On the Environmental Challenges of Economic Development in Indonesia

Fevriera, S.

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geboren te Salatiga, Indonesië

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Sotya Fevriera
Salatiga, August 2020

CHAPTER 1 Introduction

1.1 Background

Global warming is an increasing concern across the globe. Awareness is rising that greenhouse gas emissions (GHGs) pose a serious problem causing increasing average temperatures resulting in floods, landslides, reduced harvests, extreme weather events, forest fires, etcetera. Progress on fighting climate change so far has been limited, despite clear ambitions defined in annual Conferences of Parties, the most notable ones resulting in the Kyoto protocol in 1997 and the Paris agreement in 2017. A large-scale shift to low-carbon energy supplies is crucial for avoiding dangerous levels of climate change.

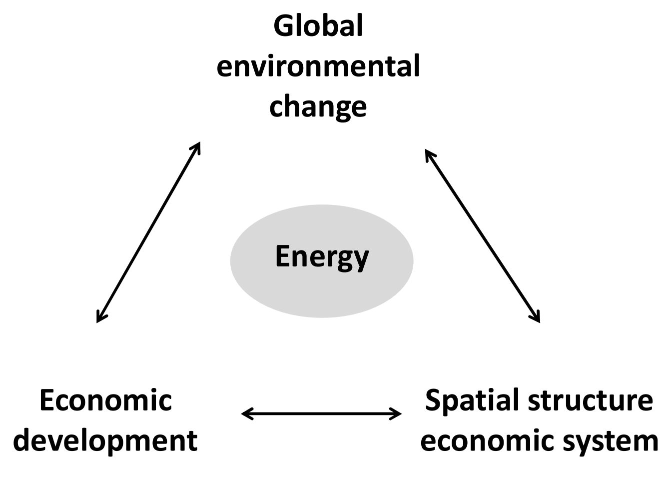
For several reasons, countries in the global South play a crucial role in achieving the ambitions to mitigate global climate risks. Energy production and use account for two-thirds of global greenhouse gas (GHG) emissions and cities are associated with around 70% of global energy consumption and energy-related GHG emissions (GCEC, 2014). At present, developing countries account for more than two-fifths of world GDP and for most of global economic growth. The Asia-Pacific region is the leader in terms of global growth, but growth on the African continent is also higher than the global average growth rate. Around 1.4 million people are being added to urban populations each week, and 90% of this urban growth is projected to take place in the developing world (GCEC, 2014). Consequently, the growth of global GHG emissions is nowadays largely driven by developing countries (Jakob et al., 2014): since 2008 the aggregate energy-related CO_2 emissions of developing countries surpassed those of industrialized and transition countries (IEA, 2010).

In the global South, many countries are in a rapid process of economic development and are rapidly catching up with developed countries. Associated with these economic developments that have resulted in substantial reductions in poverty are increases in the use of energy and emissions which contribute to climate change. Over the last two decades, the world energy demand was forecasted to increase by 2% per annum, but after 2025 it is projected to decrease to 1% per year with the largest part of this growth stemming from developing and emerging economies in

Asia (60 percent), Africa, the Middle East and Latin America (IEA, 2014). However, these rapid developments in emerging economies also create opportunities, provided that new technologies are adopted reflecting state of the art environmentally friendly techniques and processes. In addition, many of the negative consequences of climate change are most strongly felt in developing countries providing an additional call for action. A challenge that is also clearly articulated in the United Nations Sustainable Development Goals is to allow these countries to economically catch up with the West without asking too many sacrifices in terms of environmental quality.

Cities are key when it comes to concerns regarding the feasibility of long-run environmentally sustainable growth. As economies develop, the spatial distribution of population, employment and production changes. Urbanization is probably the most prominent feature of this spatial transformation. The geography of economic activity affects growth and vice versa: an economy's degree of urbanization is not only a consequence of its development, but it also determines its growth (Desmet & Henderson, 2014; Motamed et al. 2014). Therefore, future global environmental change not only depends on the stage of development but also on the (changing) spatial structure of the economic system that emerges in the course of economic development (see Figure 1.1).

Figure 1.1 – The Interplay between Development, Space and the Environment



Clearly, because of the spatial inertia of infrastructure and the built environment, current choices regarding the spatial structure of economic development create strong path dependencies that will shape the future impact of urbanization on local energy use and global climate change. While spatial development is driven to a large extent by market forces, there is an important role of government policies and planning for both the location and the concentration of economic activities in space (Desmet & Henderson, 2014). However, most research into the question of how GHG emissions can be curbed without harming development prospects ignores the spatial structure of both economic development and environmental degradation. For example, much attention has been devoted to the so-called Environmental Kuznets Curve (EKC), an inverted U-shaped relationship that may exist – the empirical evidence is still subject to debate – between the level of pollution (like GHG emissions) and the level of economic development. Prominent explanations for such a potential relationship include technological innovation in (emission) pollution control, structural change towards a service-based economy ('de-industrialization') and income driven shifts in preferences and environmental policy (Selden & Song, 1994). Clearly, these mechanisms have a spatial dimension, but virtually all EKC studies are one-dimensional: they consider the role of time, but not of space (the left arrow in Figure 1.1).

As already noted, developing countries play a key role when it comes to the need of reconciling expansion of the world economy with global environmental sustainability. However, most research on the relationship between energy use and the spatial structure of economic development focuses on developed countries. For example, most studies that analyze energy use under the influence of urbanization implicitly assume that contemporary urbanization patterns in developing countries processes share many similarities with the urbanization process of today's developed countries in the 19th century (see, for example, Jones, 1989, Poumanyvong & Kaneko, 2010; Sadorsky, 2013). However, there are good reasons to believe that contemporary urbanization processes in developing countries differ in several important dimensions. First, they are much faster in today's developing world, taking roughly half the time(!) of historical urbanization processes in Europe. Second, while income growth remains the main driver of urbanization, urban income levels do not rise quickly enough and we increasingly see an urbanization of poverty (Fay & Opal, 2000). Third, the cities in developing countries are much larger: Lagos, Manila and Jakarta are urban super-giants compared to European or North American cities at the time that their GDP per capita levels were comparable to contemporary levels in developing countries. Obviously, these facts have critical implications for the interrelationships between economic development, economic geography, and environmental changes, and in particular the (long-run) impact of urbanization on energy use (cf. Madlener & Sunak, 2011). Therefore, understanding the involved mechanisms is crucial in answering the question whether the emergence of developing economies can be reconciled with global environmental sustainability.

This thesis aims to contribute to the study of interactions between global environmental change, economic development and the spatial structure of the economic system in developing countries. We focus our research on Asian countries, with a specific focus on Indonesia.

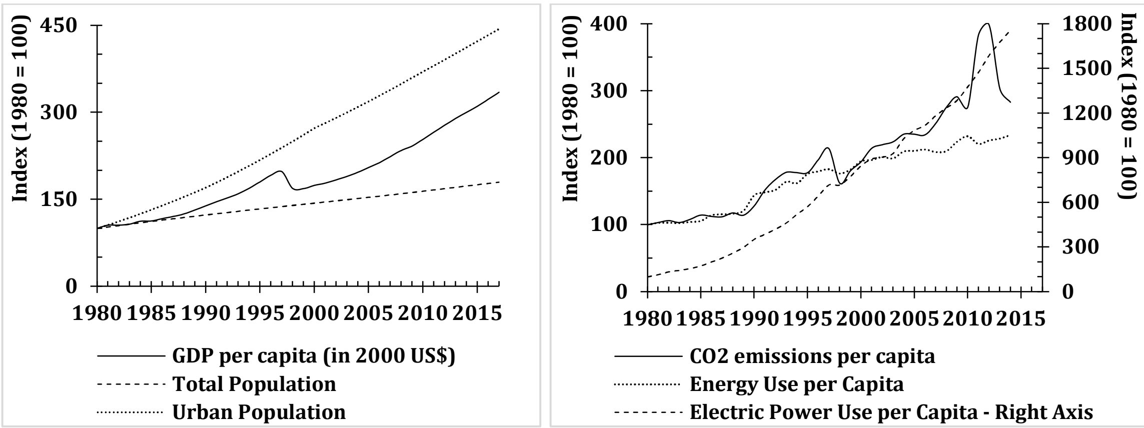
1.2 Indonesia

Indonesia contributes to the global GHG emission increase through various channels. Indonesia's population in 2017 (264 million inhabitants) was the fourth biggest in the world and between 1960 and 2017 the population of Indonesia grew faster than that of the world (201 percent versus 148 percent, respectively) (World Bank, 2018). In 2016, Indonesia's per capita GDP (in constant 2011 international $) was lower than the world average. However, during the period from 1990 to 2016 Indonesia's per capita GDP grew more rapidly than the world's average (133 percent versus 69 percent, respectively). Between 1971 and 2014, the energy use of Indonesia grew with 543 percent while the world's energy use 'only' grew with 178 percent (World Bank, 2018). It reflects that Indonesia's economy developed relatively favorably during the past decades. Indonesia's energy intensity[1] in 2014 was lower than that of the world, indicating that energy use in Indonesia was relatively energy extensive. During the period from 1990 to 2014, Indonesia's energy intensity declined with 25 percent corresponding to 1.2 percent per year. The decline suggests that during this period, the energy use in Indonesia became more efficient. However, the reduction in Indonesia was slower than that in the world. For the same period, the world's energy intensity decreased with 30 percent corresponding to 1.5 percent per year.

[1] Energy use (kg of oil equivalent) per $1,000 GDP (constant 2011 PPP).

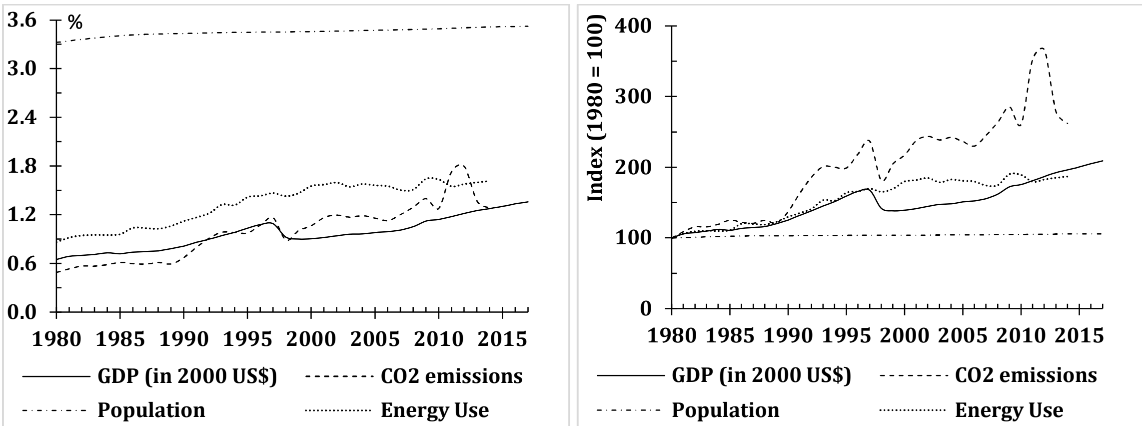
These developments in Indonesia are summarized in Figures 1.2 and 1.3. The left panel of Figure 1.2 reveals the steady increase of the population, the rapid economic development only interrupted by the crisis in the late 1990s and the rapid urbanization, especially in the early 1990s. The right panel of Figure 1.2 reveals the steady increase of electrical power use per capita. Energy use took of especially in the early 1990s whereas we see an increase of the CO_2 intensity of the energy production in especially the first decade of the 20th century.

Figure 1.2 – The Dynamics of Indonesia, 1980–2017



Data Source: World Development Indicators (World Bank, 2018).

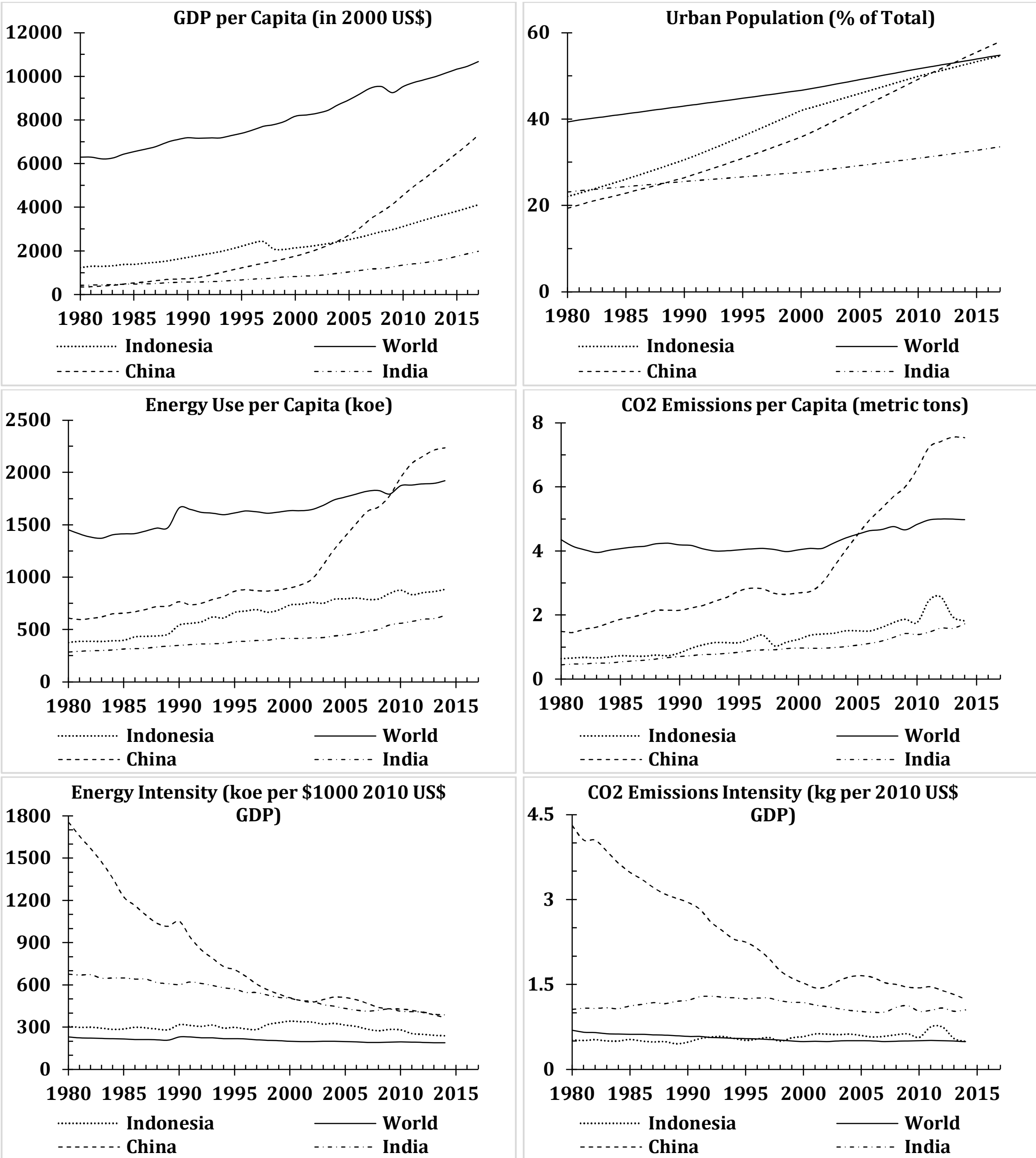
Figure 1.3 – Share of Indonesia in World, 1980–2017



Data Source: World Development Indicators (World Bank, 2018). The left picture shows a fraction of the world total; the right picture is an index (1980=100).

The left panel of Figure 1.3 looks at the share of Indonesia in the world economy, whereas the right panel shows that same share, but now as an index. It clearly reveals the relatively strong increase of the contribution of Indonesia in the world CO_2 emissions.

Figure 1.4 – Indonesian Dynamics in Global Perspective, 1980–2017

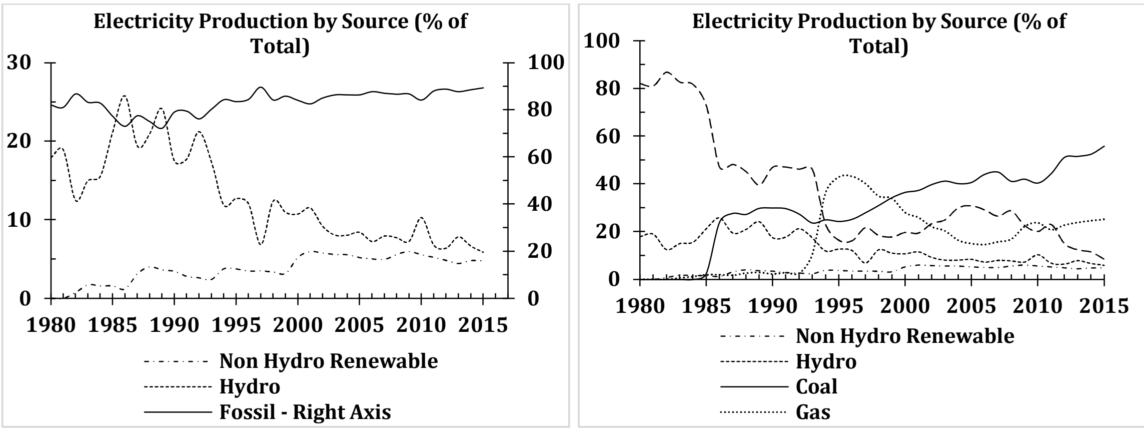


Data Source: World Development Indicators (World Bank, 2018).

In line with the insights from the literature on the Income-Emission Relationship (oftentimes popularly referred to as the Green Kuznets Curve literature; see Chapter 2 of this thesis), the main elements behind the increase in energy use are the increases in population and income per capita. Population affects energy use since larger populations – ceteris paribus – consume more energy. Per capita GDP affects energy use since energy is needed to support economic activities. Technological progress tends to negatively affect the amount of energy that is needed per unit of output and the sectoral composition of economies typically changes in favorable environmental directions as preferences tend to shift towards more environmentally friendly products as people become richer (e.g., De Groot, 1999).

Figure 1.4 places these developments in Indonesia in an international perspective. Figure 1.5 zooms in on the energy situation of Indonesia. It shows that fossil fuels remain a crucial source for electricity production with around 90 percent. Over time, we witness a switch from oil to coal. Non hydro renewables are only a small share, while hydro is even declining in importance.

Figure 1.5 – Indonesian Electricity Production by Source, 1980–2015



Data Source: World Development Indicators (World Bank, 2018).

1.3 Setup of the Thesis

In this thesis, we study the interactions between global environmental change, economic development and the structure of the economic system requires from different perspectives, building on different lines of literature that focus on different aspects of the complex interrelationships.

The previously described developments in Indonesia have already caught the interest of several researchers. Table 1.1 summarizes studies on the Income-Emission Relationship for Indonesia. Chapters 2 and 3 of this thesis expand on these studies dealing with the relationship between economic development and environmental degradation in various ways. Chapter 2 develops a meta-analysis of previously published empirical studies on the Environmental Kuznets Curve (EKC) to shed new light on the long-lasting debate on the income-emission relationship (IER). More specifically, we aim to explain the sources of variation in the shape of the EKC and its turning points. In contrast to previous meta-analyses of the EKC, we focus on CO_2 emissions, construct a dependent variable that allows for more diversity in the shape of the income-emission relationship (IER), focus on the turning points that characterize the IER and use an ordinal logit model to study the IER, in contrast to earlier studies that used a multinomial logit model.

Chapter 3 aims to identify the role of cultural values in a society in determining income–emission relationships (IERs) across a sample of Asian economies. The culture of a society can be defined as a set of information that is equitably owned by all the members of society who embrace that culture and use it as their reference in all of their actions and behaviour (Sasmojo, 2004). Since CO_2 emissions result from human activities, cultural values can be thought of as (implicit) drivers of CO_2 emissions. The inverted U-shaped pattern that characterizes the EKC is also often implicitly assumed to be driven by cultural values through their impact on people's preferences. The idea is that, in the early phase of economic development, the environmental quality may decline, because people are unwilling to trade consumption for investment to improve the environmental quality. However, at higher income levels, the cultural preferences for substituting consumption for investment to prevent environmental degradation are thought to change gradually. As economies develop, awareness of environmental problems increases, which translates into environmental policies and the increased use of relatively environmentally friendly technologies. In addition, the cultural values of a society play a role in determining its ability in science and technology (Sasmojo, 2004), because the private and public institutions of a country reflect its culture. Often, the identification of a culture is reserved for a society such as a nation (Hofstede, 2001). Hence, in chapter 3 we hypothesize that cross-country differences in cultural values can (partly) explain differences in emission intensity across countries. Together with the structural economic changes that accompany economic development, cultural values may explain the non-linear patterns of the IER – such as the EKC – that often appear to exist (Moomaw & Unruh, 1997).

Table 1.1 – Previous IER Studies on Indonesia

Authors	Type of Data	Dependent Variable	Independent Variable	Method	Some Findings	Conclusion on EKC
Dariah (2007)	Time series data of West Java rovince, IDN, 1974– 2004	• CO emissions CO) • per capita CO_2 emissions (CO_2)	• per capita real GRDP (YT) • The existence of policy on air pollution control (DLU) • environment awareness = mean years of schooling (ED) first lag variable • First lag variable of CO • First lag variable of CO_2	• Environment-macroeconomics model which consists of 12 structural equations & 8 identities. • YT was displayed in linear relationship with CO and CO_2.	• YT & first lag variables have a positive significant effect on CO & CO_2.	untested
Hutabarat, L. (2010)	Panel data of IDN, MYS, PHL, SGP & THA 1980– 2000	• per capita CO_2 • emissions (CO_2) • per capita sulfur emissions	• GDP of industry sector	Fixed Effect Model	• EKCs are proved for CO_2 and sulfur	confirmed
Hakim, D.B. (2011)	Panel data of IDN, MYS, THA, VNM 1986-2007	per capita CO_2 emissions (CO_2)	• per capita GDP (GDP) • Foreign Direct Investment (FDI) • trade openness (TRADE)	Fixed Effect Model	• EKC is not proved. • The linear effect of GDP has a positive significant effect on CO_2. • TRADE has a positive significant effect on CO_2.	rejected
Shofwan & Fong (2011)	Time series data of IDN, 1975– 2009		• CO_2 emissions • real GDP • population	Spearman correlation analysis.	• A negative moderate significant correlation between CO_2 emissions & real GDP exists. • A positive very strong significant correlation between CO_2 emissions & population exists.	untested
Idris (2012)	Cross-sectional data of IDN provinces, 2008	Air Pollution Index which represents SO_2 & NO_2 emissions	per capita GRDP	Regression analysis with quadratic function relationship.	EKC is not proved.	rejected
Bowo, P.A. (2012)	Data from Central Java province, IDN	CO emission (CO)	per capita GRDP (GRDP)	• Quadratic relationship. • All variables were transformed in LN	• EKC is claimed to be proved but only based on the effect sign of CO on the quadratic GRDP	confirmed

Table 1.1 – Previous IER Studies on Indonesia (continued)

Authors	Type of Data	Dependent Variable	Independent Variable	Method	Some Findings	Conclusion on EKC
Jafari, et al. (2012)	Annual time series data of IDN, 1971– 2007		• real GDP • energy consumption (EC) • CO_2 emissions • urban population (UPOP) • capital stock	• The long run Granger causality relationship. • All variables were transformed in LN.	• Unidirectional causal relationship from UPOP to EC exists. • The EKC hypothesis may not apply to IDN.	untested
Saboori. et al. (2012)	Time series data of IDN, 1971– 2007	per capita CO_2 emissions (E)	• per capita real GDP (Y) • commercial energy consumption per capita (EN) • trade openness (TR) = ratio of total real import & export to real GDP	• The ARDL methodology. • All variables were transformed in LN. • Relationship between E & Y is in quadratic form.	• Y has significant effects in short & LR models but no evidence of EKC (relation between Y & E is U-shape). • EN has a positive significant effect in SR & LR models. • TR has a positive significant effect in LR but insignificant effect in SR models.	rejected
Saboori & Sulaiman (2013)	Annual time series data of IDN, MYS, PHL, SGP and THA 1971– 2009	per capita CO_2 emissions (E)	• per capita real income (Y) • energy use per capita (EN)	• The ARDL methodology and the Granger causality based on VECM. • All variables were transformed in LN. • Relationship between E & Y is in quadratic form.	• In all ASEAN countries, positive significant relationship and a bi-directional Granger causality between EN and E exist in the SR & LR models. • In IDN and PHL, Y has a significant effect in SR & LR models but the EKC hypothesis is unproved (relation between Y & E is U-shape). • EKC exists in the SR & LR models in THA and in the LR model in SGP. • A LR bi-directional Granger relationship between Y and E exists in IDN, MYS & PHL. • A SR bi-directional Granger relationship between Y and E exists in IDN, SGP & THA.	confirmed for SGP and THA, but not for IDN
Shahbaz, et al. (2013)	Quarter frequency data of the IDN economy, 1975– 2011	per capita CO_2 emissions (C)	• energy consumption per capita (E) • real GDP per capita or economic growth (Y) • financial development (F) = real domestic credit to private sector per capita • trade openness per capita (TR)	• VECM Granger causality technique to examine the causal relation between the concerned variable. • All variables were transformed in LN. • Y was displayed in linear relationship whilst F was displayed in linear & quadratic relationship with C.	• E & Y have a positive significant effect in SR & LR models. • TR has a negative significant effect in SR & LR models. • In model with linear relationship for F, F has a negative significant effect in the LR model but in the SR model F has a positive significant effect. • Bidirectional causal relationships between E & C, Y & C and TR & C exist. • Unidirectional causality from F to C exists.	not tested

Table 1.1 – Previous IER Studies on Indonesia (continued)

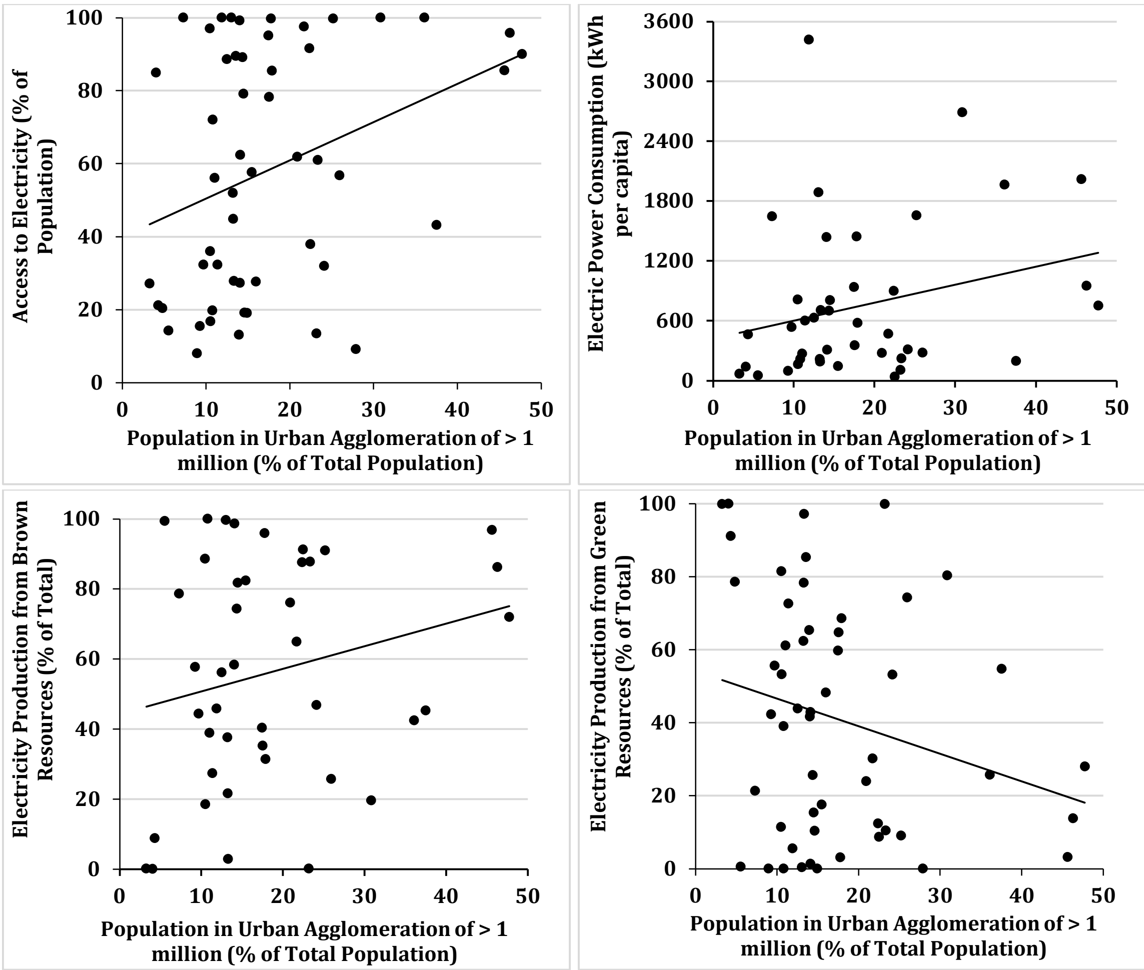
Authors	Type of Data	Dependent Variable	Independent Variable	Method	Some Findings	Conclusion on EKC
Fevriera, et al. (2013)	The world panel data 1971– 2009	First stage of analysis: • CO_2 emissions (co_2) • CO_2 emission intensity = co_2 per • energy use (co_2int) Second stage of analysis: • The intercepts of the curve estimation of the CO_2. • The intercepts of the curve estimation of the CO_2int.	First stage of analysis: • per capita real income (gdpcap) • population (pop)Second stage of analysis: • gasoline price (gasoline) • Logistic Performance Index (LPI) • proportion of clean energy (clean) • The Masculinity Index (MAS) • The Power Distance Index (PDI) • The Uncertainty Avoidance Index (UAI) • The Individualism Index (IDV)	• Countries and time fixed effects for the first stage of analysis. • Ordinary Least Square model for the second stage of analysis. • gdpcap and pop were transformed in LN. • gdpcap was displayed in cubic relationship with co_2 and co_2int.	• EKC is proved for co_2 or per capita co_2 but not for co_2int. • The linear effect of gdpcap has a significant effect on co_2int. • pop has a positive significant effect on co_2. • The elasticity of co_2 to population is unitary. gasoline has a negative significant effect on co_2. • LPI has a positive significant effect on co_2. • Clean has a negative significant effect on co_2 and co_2int. • UAI has a negative significant effect on co_2int. • IDV has a positive significant effect on co_2int.	confirmed
Hwang & Yoo (2014)	Time series data of IDN, 1965-2006	• energy consumption (E) • CO_2 emissions (C) • real GDP (Y)		• The Granger-causality based on an error-correction model. • All variables were transformed in LN.	• A bi-directional causality between E and C exists. • A uni-directional causality running from Y to E and C exists.	Untested
Sugiawan & Managi (2016)	Time series data of IDN, 1971-2010	• CO_2 emissions (C)	• per capita real GDP (Y) • electricity production from Renewable resources (ER) • energy consumption (EC) • total factor production (TFP)	• The ADRL-bounds testing.	• The EKC is proved in the long-run quadratic model but not in the hort-run model. • Negative significant effect of ER. • Positive significant effect of EC.	confirmed
Diputra & Baek (2018)	Time series data of IDN, 1973-2013	• CO_2 emissions (c)	• per capita real GDP (y) • per capita energy consumption (er) • percentage of urban Population (urb)	• The ADRL model	• The EKC is proved in the long and short run quadratic model. • er has positive and negative significant effects in the long & short run models. • urb has a negative significant effect in the short-run model.	Confirmed

Notes: IDN = Indonesia, MYS = Malaysia, PHL = Phillippines, SGP = Singapore, THA = Thailand, VNM = Vietnam, LN = natural logarithm, LR = long-run, SR = short-run

In Chapters 4, 5 and 6 we focus on the role of cities in defining the interaction between global environmental change, economic development. The transition to a predominantly urban human population will have a significant impact on the emerging transition to a low-carbon energy system, because there are fundamental physical limits to how much energy we can extract from renewable resources for a given area of land. In Chapter 4 we deal with this issue in the context of urbanization trends in Indonesia. To this aim, we introduce the concept of an energy source's power density in watts per square metre (W/m^2). Power density is a measure of a resource's 'spatial productivity'. High power density allows for concentration of people and firms in space (Moreno-Cruz & Taylor, 2012; Wilson, 2013; Smil, 2015). Following the recent work by Moreno-Cruz & Taylor (2012, 2014, 2017), we develop in Chapter 4 a spatial energy model that builds on the concept of power density to analyze the potential trade-off between greening and brown expansion of the electricity supply in developing countries under the influence of increasing population density. We calibrate the model to the case of Indonesia.

The dual challenge of expanding and greening the electricity supply relates to the degree of urbanization. Figure 1.6 shows that across low income and lower-middle income countries (per capita Gross National Income below $3,955) both access to electricity and per capita electric power consumption are positively correlated with concentration of population in urban agglomerations of more than 1 million people (see top left and top right of Figure 1.6). Also, concentration of population in large agglomerations is positively correlated with electricity production from brown (non-renewable) resources (see bottom left of Figure 1.6), while the opposite is true for electricity production from green (renewable) resources (see bottom right of Figure 1.6). In most low and lower middle-income countries, green resources are responsible for only a very small fraction of electricity production, i.e. less than 58% (see bottom right of Figure 1.6). However, in some low and lower middle-income countries, green resources are responsible for a substantial part of electricity production (exceeding 90%). In those countries, population concentration in large agglomerations is less than 25% of the total population (see bottom right of Figure 1.6).

Figure 1.6 – Concentration of People in Low and Lower-Middle Income Countries, in Relation to Electricity Access and Consumption (Top) as well as Electricity Production from Non-Renewable and Renewable Sources (Bottom)



Notes: Brown resources = oil, gas and coal sources. Green resources = renewable sources, including hydropower. Data Source: World Bank Development Indicators (World Bank, 2017).

Currently around 14% of the Indonesian population lives in agglomerations over 1 million, up from 8% in the 1970s. And this process is expected to continue with potentially far reaching challenges and opportunities in view of the energy transition. It is our objective to identify how and to what extent the spatial distribution of population and economic activities influences the urban energy transition.

As people urbanize and households become more affluent, patterns of consumption, commuting, housing and fuel mix change. Regarding the latter, as incomes rise residents switch fuels towards modern energy sources like electricity and natural gas (Barnes et al., 2005). In Chapter 5 we analyze urban energy use patterns across Indonesia. More specifically, we first investigate whether urbanization influences the per capita energy consumption, controlling for the impact of urbanization on per capita incomes. To achieve this aim, we develop an instrumented 2-stage regression method, which we apply to a cross-city dataset for 71 Indonesian cities that was constructed from existing household surveys and census data. In addition, we analyze the spatial patterns of energy consumption across districts within the metropolitan area of Yogyakarta, one of Indonesia's largest cities. We conducted a survey on energy consumption and travel behavior among 748 households in Yogyakarta Province. The individual dimension of the survey data allows us to evaluate the extent to which the observed impact of urban indicators on energy consumption is influenced by the spatial sorting of people across districts in Yogyakarta Province. We use an estimation strategy that is inspired by the approach that Combes et al. (2008) developed to control for worker heterogeneity in explaining spatial wage disparities across local labor markets in France.

Finally, in Chapter 6 we analyze the way in which urban form influences preferences for the use and ownership of motorcycles, using the results from a field study conducted in the metropolitan area of Yogyakarta in Indonesia. Across all of Asia, the number of motorcycles in urban road traffic is much higher than the number of passenger cars – as shown in Table 6.1. Almost 80% of the world's motorcycles can be found in Asia (ITF, 2008). Many governments in Asian countries have been trying to encourage people to reduce their usage of private motorized vehicles and to change to public transportation or non-motorized transport modes to decrease the energy consumption and emissions from transport.

CHAPTER 2 What Drives the Environmental Kuznets Curve for CO_2 Emissions? A Meta-Analysis

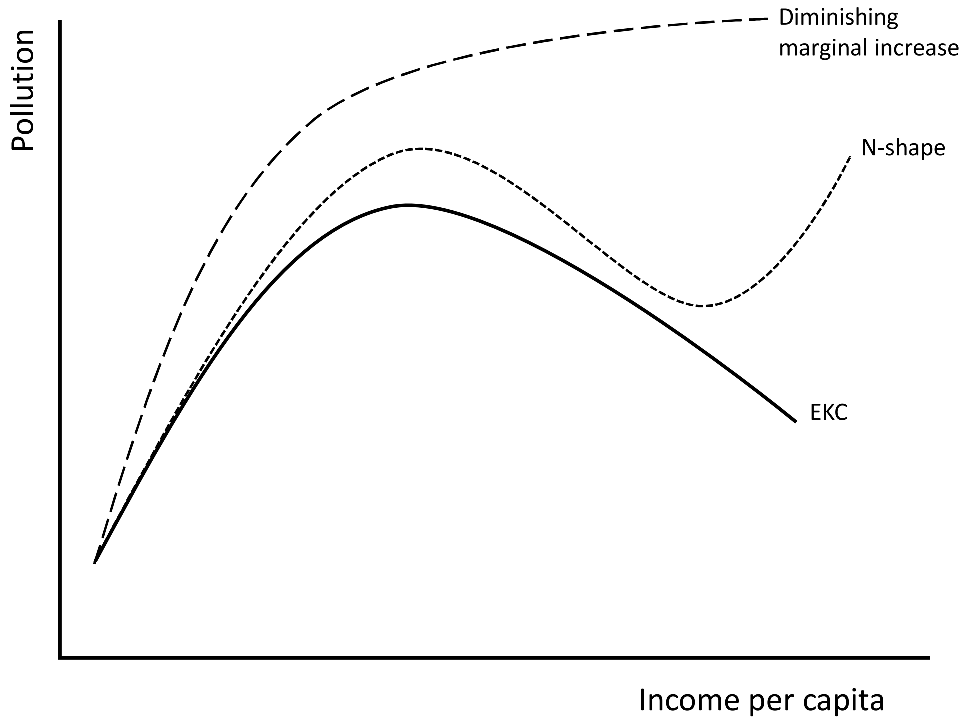
2.1 Introduction

Economic development and global environmental change are strongly interrelated. In the body of literature that has studied the relationship between economic development and environmental degradation, much attention has been devoted to the so-called Environmental Kuznets Curve (EKC): a hypothesized inverted U-shaped relationship between the level of pollution (measured by, for example, GHG emissions) and the stage of economic development (typically proxied by GDP per capita) (see Figure 2.1). The idea was introduced by Grossman & Krueger (1992) and is named after Simon Kuznets (1955), who hypothesized that income inequality first rises and then falls as economic development proceeds. Prominent explanations for such a relationship between economic development and pollution have built on technological innovation in (emission) pollution control, structural change towards a service-based economy ('deindustrialization') and income-driven shifts in preferences and environmental policy (Selden & Song, 1994; Moomaw & Unruh, 1997; De Groot, 1999; Smulders et al., 2011). However, the empirical evidence for the existence of the EKC is still subject to debate – partly because different studies have used different samples of countries, time periods, pollutants and econometric methods (Dasgupta et al., 2002; Stern, 2004).

In the literature, alternative views on the shape of the income–emission relationship have been suggested, including an N-shaped curve and monotonically rising pollution levels with an income elasticity less than one (see Figure 2.1). The various IER curves accommodate the debate between those who found that the EKC exist (see for example Heerink et al., 2001; Kahuthu, 2006; Halkos & Paizanos, 2013) and those who not (see for example Day & Grafton, 2003; Lipford & Yandle, 2010; Wang, 2012). Some studies which applied model for some different countries or pollutant indicators also found conflicting findings (see for example Yaguchi et al., 2007; Fodha & Zaghdoud, 2010; Mazzanti & Musolesi, 2013). The debate also represents different views between pessimistic and optimistic environmental scientists. Pessimistic environmental scientists think that it is difficult to regenerate natural resources so natural resources decrease in term of quantity and quality and that the development of technology will not be able to prevent the increase of environment deterioration. On contrary. optimistic environmental scientists think that human has a capability to adapt in order to prevent the environment to become worse and to create technology to improve the environment, including how to regenerate natural resource.

This chapter develops a meta-analysis of previously published empirical studies on the Environmental Kuznets Curve (EKC). More specifically, we aim to explain the sources of variation in the shape of the EKC and its turning points. In contrast to previous meta-analyses of the EKC, we focus on CO_2 emissions, construct a dependent variable that allows for more diversity in the shape of the income–emission relationship (IER), focus on the turning points that characterize the IER and use an ordinal logit model to study the IER, in contrast to earlier studies that used a multinomial logit model.

Figure 2.1 – The Environmental Kuznets Curve (EKC) and Alternative Hypotheses



This study conducts a meta-analysis to shed new light on the long-lasting debate on the income–emission relationship (IER). Meta-analysis has been used before to summarize the evidence for an EKC (Cavlovic et al., 2000; Li et al., 2007; Koirala et al., 2011; Goldman 2012). Our study differs from these meta-analyses in several respects. First, in contrast to the aforementioned studies, we focus on CO_2 emissions as the main source of global warming,[2] whereas most other meta-analyses of the EKC have focused not merely on CO_2 emissions but on various pollutants. Using only CO_2 emissions as the indicator for environmental degradation improves the comparability of the results, which is relevant for any meta-analysis. Second, we construct a larger dataset than ever before, covering substantially more studies: we have a total of 919 observations from 136 studies. Furthermore, we develop a dependent variable with a more refined classification of the possible shapes of the income–emission relationship that can better characterize the richness in the outcomes of primary studies. Finally, in contrast to the existing meta-analyses, we apply an ordered logit (ORL) model when the dependent variable is the shape of the IER and an OLS model when the dependent variable is the turning point of the IER. We differentiate the turning point values in relation to whether they refer to a maximum turning point or a minimum turning point.

The remainder of this chapter is structured as follows. In section 2.2, we discuss the usefulness of meta-analyses in the field of EKC studies and compare the existing studies with our approach. In section 2.3, we present our methodology and the construction of our dataset in more detail. In section 2.4, we present the results of our analysis. Section 2.5 concludes.

2.2 Meta-Analysis and Its Application to EKC Studies

The preliminary idea of meta-analysis originated from Blaise Pascal's development of a mathematical method to estimate the probability result of a gamble from various observations in the seventeenth century. A simple meta-analytical approach was first applied in medical research by Karl Pearson to integrate data from various studies of disease and death of soldiers who received injection treatments for typhoid fever

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[2] According to the World Resource Institute, the share (excluding land use change and forestry) of CO_2 emissions in greenhouse gases (GHGs) in 2012 was 76% (WRI, 2015).

(O'Rourke, 2007). For research in the field of health, the meta-analysis procedure that takes into account the results from many cases is very useful, because it may increase the ability to identify small clinically significant effects (Crombie & Davies, 2009). Although originating in the medical sciences, recently meta-analysis has been used in a wide array of other fields, such as agriculture, sociology, economics and education (see Dalhuisen et al., 2003; De Groot et al., 2004; Boys & Florax, 2007; Ridhwan et al., 2010, for examples in various fields).

Meta-analysis provides researchers with a toolkit to summarize findings and detect heterogeneity in the outcomes obtained from a set of comparable primary studies. It can furthermore be used to identify sources of heterogeneity in the outcomes (DerSimonian & Laird, 1986; Florax et al., 2002; Dinda, 2004). Gene V. Glass (1976) introduced the term 'meta-analysis', which refers to an analysis of results from (many) previously conducted primary studies using statistical tools. A meta-analysis that employs regression analysis to analyse regression models from previous studies is called a meta-regression analysis (MRA) (Stanley et al., 2008).

Meta-analysis can complement qualitative or narrative literature reviews, which typically at best only allow for a simple quantitative analysis presenting basic descriptive statistics, such as displaying the results (e.g. positive significant, negative significant and insignificant) as (relative) frequencies with a technique known as vote counting or by contrasting the results, for example comparing elastic, inelastic and unit elastic demand or supply (Dalhuisen et al., 2001; Florax et al., 2002; Boys & Florax, 2007). Compared with the more traditional literature reviews, meta-analysis is more objective and transparent (Florax et al., 2002; Boys & Florax, 2007; Van Bergeijk & Lazzaroni, 2015). Another and related important advantage is that it can correct for publication selection bias, which comes from the subjective preferences for particular studies and variables included in the research, as people tend to choose studies with large and statistically significant results (Stanley, 2008). Meta-analysis also enables us to develop a multivariate framework, because it enables us to use aggregate data that cannot be used in individual studies (Groot & van den Brink, 2000) and allows non-sampling characteristics, such as the research design, model specification and estimation technique, to be moderator or predictor variables (Dalhuisen et al., 2001; Florax et al., 2002). Meta-analysis gives a summary of independent variables from previous studies that may explain the dependent variable better, and it enables us to estimate the marginal effects (Florax et al., 2002). It can compare quantitative studies with difference methodology that are relevant with the method that is used in the meta-analysis and can be used to compare difference impact of studies with various methodology (Van Bergeijk & Lazzaroni, 2015).

A meta-analysis is, however, not without limitations. First, it cannot be used to compare qualitative analysis and case studies and cannot include incomplete studies (Bergeijk & Lazzaroni, 2015). Second, there is a difficulty in determining how to collect a representative sample of studies that will be used as the meta-analysis sample. Journals tend to reject papers that cannot provide evidence to support the hypothesis on the effects of the studied variables, while meta-analysis needs the 'heterogeneity' findings to obtain a representative sample of the population of studies (Florax et al., 2002). The third problem concerns the handling of differences in the studies used as the sample in the meta-analysis. The meta-analysis sample comes from studies with different data quality and characteristics, such as different data sources, different unit measurements, different data periods and different research methods, for instance different types of regression model used in the studies (Florax et al., 2002). Since we are more interested in the shape of the IER than any single metric, we refer to the study by Ridhwan et al. (2010), who conducted a meta-analysis to investigate the impulse response functions characterizing the economic impact of a financial shock. The third problem with meta-analysis is that it usually ignores the independence of the sample observations. Meta-analysis could obtain several observations from one study. Since those observations come from the same study, they are not independent (Florax et al., 2002).

The first meta-analysis of EKC studies was conducted by Cavlovic et al. (2000) and followed by Li et al. (2007) and Koirala et al. (2011). The study by Li et al. (2007) was replicated by Goldman in 2012. Those studies used EKC research with various pollutants as the indicators of environmental degradation, including CO_2 emissions. Choumet et al. (2013) then performed a meta-analysis of EKC studies with only deforestation as the environmental degradation indicator. Table 2.1 compares our study with previous studies (with the exception of Choumet et al. (2013), because we have a different indicator of environmental degradation).

In conducting their meta-analyses, Li et al. (2007), Cavlovic et al. (2000), Koirala et al. (2011) and Goldman (2012) used different models and dependent variables (see Table 2.1). Goldman (2012) categorized the shapes of the IERs into several groups and used the multinomial logit (MNL) model. All the independent variables were tested to determine whether they have a significant impact on the dependent variable using one category of the IER shape as the reference, that is, the *ELSE* category. Cavlovic et al. (2000) employed the tobit and generalized least squares (GLS) models with the values of turning points as the dependent variable. Li et al. (2007) and Koirala et al. (2011) used both types of dependent variable, namely the shape of the IER and the turning point value. When the dependent variable is the shape of the IER, Li et al. (2007) and Koirala et al. (2011) used the MNL model, and, when the dependent variable is the turning point value, Li et al. (2007) employed the Tobit model, whereas Koirala et al. (2011) applied the ordinary least squares (OLS) and tobit models. In this study, we also utilize both types of dependent variable, but we apply the ordered logit (ORL) model when the dependent variable is the shape of the IER and the OLS model when the dependent variable is the turning point. We differentiate the turning points into maximum turning points and minimum turning points. This is in contrast to Li et al. (2007), Cavlovic et al. (2000) and Koirala et al. (2011), who did not distinguish between the types of turning point. By making this distinction, we can more easily identify the factors that contribute to finding an increasing IER by focusing on those studies with a minimum turning point.

Table 2.1 – Differences from Previous Studies

Comparison	This Study	Cavlovic et al. (2000)	Li et al. (2007)	Koirala et al. (2011)	Goldman (2012)
Database	• 919 observations from 136 studies (published articles or a book)	• 121 observations from 25 studies	• 588 observations from 77 studies	• 878 observations from 103 studies	• 155 observations from 25 studies
Pollutant	• CO_2	• Toxic • Urban air (smoke/dark matter) • Deforestation/afforestation/park area • Suspended/heavy particles • Urban sanitation/safe (drinking) water/fecal coliform • BOD/COD/dissolved oxygen/nitrates • Heavy metals • SO_2 • Carbon monoxide/nitrogen oxides • Hazardous waste • CO_2	• Anthropogenic activity-related GHG • Chemical-active GHG • Biologically related pollutants	• CO_2 • SO_2 • NO_X • Active gas (sulphur/C/CFC/CO/O_2) • VOC, CH_4, unburned energy and other air pollution • Smoke, TSP, particles, SPM_tran and PM10 • Lead, arsenic, hazardous waste, cadmium, mercury, nickel and HWS • BOD, COD, DO, coliform and other water pollution • Deforestation, loss of habitat/biodiversity and park degradation • Waste from houses, rents, food and municipal waste • Environmental degradation that includes agricultural by-products or waste resulting from the processing of agricultural commodities, which include by-products of meat processing and agricultural produce • Other pollutants	• Anthropogenic activity-related GHG • Chemical-active GHG • Biologically related pollutants
Model	a. Ordinal logit model for *SHAPE* b. OLS model for TP_{max} and TP_{min}	• Weighted censored tobit and GLS models	a. Multinomial logit model for *RELATION* b. Weighted tobit model for *ITP00*	a. Cluster multinomial logit model for EKC *RELATIONSHIP* b. Cluster OLS and cluster tobit models for ITP	• Multinomial logit model for *RELATION*

Table 2.1 – Differences from Previous Studies (continued)

Comparison	This Study	Cavlovic et al. (2000)	Li et al. (2007)	Koirala et al. (2011)	Goldman (2012)
Dependent variable	a. *SHAPE* = • 6 for an IER that is monotonically decreasing • 5 for an IER with an inverted-N shape • 4 for an IER with an inverted-U shape • 3 for an IER with a U shape • 2 for an IER with an N shape • 1 for an IER that is monotonically increasing b. TP_{max} of the environmentally friendly curve c. TP_{min} of the environmentally deteriorating curve • TP_{max} and TP_{min} for monotonic curves within the range of GDP per capita = mean of the relevant turning point within the range of GDP per capita • *TP* is the value of GDP per capita in constant 2000 US$	*ITP* = the income turning point of the IER that was taken from the paper or calculated by ignoring all higher orders than the quadratic income terms. • In the GLS model: ♦ *ITP* for monotonically decreasing curves = the logarithm value of the lowest national per capita income levels for industrializing, OPEC and other developing and developed nations ♦ Positive IER with high extreme *ITP* were not truncated from the data • In the tobit model: ♦ *ITP* for monotonically increasing curves = an upper-censored value at the logarithm value of $500,000 ♦ ITP for monotonically decreasing curves = $497.70 ♦ *ITP* is the value of GDP per capita constant in 1992 US$	a. *RELATION* = • 1 if the IER has an inverted-U shape or monotonically declining trend (*IMPROVE*) • 2 if a curve has coefficient signs that support the EKC theory but are statistically insignificant (*INSIG*) • 3 if the IER has a monotonically increasing trend, an insignificant inverted-U shape or an N shape (WORSEN) or if there is no relationship (*NONE*) b. *ITP00* = the income turning point of the IER curve (monotonically increasing, U-shaped curves and studies with no relationship were excluded) • ITP for monotonically decreasing curves = a left-censored value at the logarithm value of $3,950 (the average GDP per capita constant in 2000 for upper-middle economies) • *ITP00* is the value of GDP per capita in 2000 ppp $	a. *EKC-RELATIONSHIP* = • 1 if the IER has an inverted-U shape or a monotonically decreasing curve (*IMPROVE*) • 2 if the IER has a monotonically increasing curve (*WORSEN*) • 3 if the IER is insignificant or the relationship is undefined or if the IER has other categories (*OTHER*) b. *ITP* = the income turning point of the IER curve • In the OLS model: ♦ *ITP* = all reported *ITPs* ♦ Extremely high *ITP*s were not excluded • In the tobit model: ♦ ITP for an IER type and positive and decreasing IERs = a right-censoring limit at the logarithm value of $730,000 (determined by a sensitivity analysis) ♦ *ITP* is the value of GDP per capita in constant 2007 US$	*RELATION* = • 1 if the IER shows an environmental improvement (*IMPROVE*) • 2 if a curve has coefficient signs that support the IER theory but are statistically insignificant (*INSIG*) • 3 if otherwise (*ELSE*)

2.3 Methodology and Data

2.3.1 Methodology

As in previous meta-analyses of the IER (Li et al., 2007; Koirala et al., 2011; Goldman, 2012), we aim to explain the shape of the IER. However, in contrast to those studies, we apply the ordered logit (ORL) model instead of the MNL model. The MNL model ignores information about the ordering of the IER shape. Using the ORL model will enable us to estimate the cumulative probability of being in a category or in higher categories (versus lower categories). Our meta-analysis regression model for this objective is defined as follows:

$$(SHAPE = 1) = P(S + u \leq cut1) = \frac{1}{1+e^{-(cut1 \quad)}} \tag{2.1.1}$$

$$P(SHAPE = 2) = P(cut1 < S + u \leq \ cut2) = \frac{1}{1+e^{-(cut2)}} - \frac{1}{1+e^{-(cut1-S)}} \tag{2.1.2}$$

$$P(SHAPE = 3) = P(cut2 < S + u \leq \ cut3) = \frac{1}{1+e^{-(cut3-S)}} - \frac{1}{1+e^{-(cut2)}} \tag{2.1.3}$$

$$P(SHAPE = 4) = P(cut4 < S + u \leq \ cut4) = \frac{1}{1+e^{-(cut4 \quad)}} - \frac{1}{1+e^{-(cut3)}} \tag{2.1.4}$$

$$P(SHAPE = 5) = P(cut4 < S + u \leq \ cut5) = \frac{1}{1+e^{-(cut5-S)}} - \frac{1}{1+e^{-(cut4)}} \tag{2.1.5}$$

$$P(SHAPE = 6) = P(cut5 < S + u) = 1 - \frac{1}{1+e^{-(cut5-S)}} \tag{2.1.6}$$

with:

$$S = \sum_{j=1}^{m} \beta_j X_j \tag{2.1.7}$$

where P is a probability, *SHAPE* is an ordinal variable on the shape of the IER curve with six categories (see Table 2.2), X_j is the explanatory variable category j, β_j is the regression coefficient of variable X_j, m is the number of the explanatory variable used to estimate model (2.1.7) and *cut1*, *cut2*, *cut3*, *cut4* and *cut5* are constants that can be used to determine the changes among categories.

The *SHAPE* for equation (2.1) is defined only on the effects of GDP variables on the basis of the CO_2 emissions, ignoring the effects of other variables, and on the basis of the IER within the range of GDP per capita in the samples of our database. Our categorization differs from those of Li et al. (2007), Koirala et al. (2011) and Goldman (2012), who categorized the shapes into three groups (see Table 2.1). We divided the estimated IERs into six groups from the most 'environmentally friendly curve' to the most 'environmentally deteriorating curve', that is, a monotonically decreasing curve, an inverted N-shaped curve, an inverted U-shaped curve, a U-shaped curve, an N-shaped curve and a monotonically increasing curve. Because in this study the indicator for the environment quality is CO_2 emissions, then a curve with positive slope represents environmental deterioration and a curve with negative slope represents a friendly environment.[3] Therefore, the first three shapes are classified as environmentally friendly curves, that is, curves that are monotonically decreasing beyond a certain point, and the last three shapes are categorized as environmentally deteriorating curves, that is, curves that are monotonically increasing beyond a certain point. We make sure that all the shapes are significant by checking whether the regression coefficients that determine the shape are significant. For example, to classify an IER as an inverted-U shape or a U shape, we require the quadratic effect of income to be statistically significant.

The regression coefficient in the ORL model is the natural logarithm of the odds ratio, so the result of the ORL model is sometimes displayed in terms of odds ratios. The odds ratio is the ratio between the probability that a category or lower categories are found with the probability that higher categories are obtained or $\frac{P(\text{SHAPE} \leq i)}{P(\text{SHAPE} > i)}$. An odds ratio that is higher than one shows a positive effect of the independent variable. On the other hand, an odds ratio that is lower than one shows that the independent variable has a negative effect. The difference between one (1) and the odds ratio coefficient, that is, the antilog of the regression coefficient of the ORL model or e^{β_j}, shows the change in the odds ratio, that is, the change in the probability that a better (a more environmentally-friendly) curve is found with the probability that a worse curve is found if the independent variable changes by one unit and the other independent variables are constant.

Because there are several categories of environmentally friendly curves and environmentally deteriorating curves and the odds ratio is sometimes difficult to interpret, we also present the marginal effect $\left(\frac{\mathrm{d}Y}{\mathrm{d}X}\right)$ for each category of the shape. The marginal effect for shape category k demonstrates the average change in the probability of finding an IER with shape category k in a study with $k = 1, 2, \ldots, 6$ if the continuous explanatory variable x increases by one unit when the other explanatory

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[3] The IER shape can easily be identified by drawing its graph. In a polynomial function, an environmentally friendly curve can also be identified by the negative multiplier while an environmentally deteriorating curve can be detected by the positive multiplier of the highest degree variable.

variables are at their mean value. For a dummy variable, the marginal effect captures the percentage difference in the probability in obtaining an IER with shape category k in a situation in which the dummy takes the value one as compared with the situation in which the dummy equals zero.

We also aim to explain the turning point value of the IER curve, as in previous meta-analyses of the IER (Cavlovic et al., 2000; Li et al. 2007; Koirala et al., 2011 and Goldman, 2012). Furthermore, we differentiate the turning point values into maximum turning points and minimum turning points. Our meta-analysis regression model for this goal is defined as follows:

$$TP = \alpha_0 + \sum_{j=1}^{m} \alpha_j X_j \qquad (2.2)$$

where TP is the turning point, α_0 is the intercept model, X_j is the explanatory variables category j, α_j is the regression coefficient of variable X_j and m is the number of the explanatory variable used to estimate model (2.2).

To estimate equation (2.2), we prefer the OLS model to the tobit or GLS models, which were used by Cavlovic et al. (2000) and Li et al. (2007), whereas Koirala et al. (2011) applied both the OLS and the tobit model. They used a tobit model with an upper or left censor to include observations outside the data range with a monotonically increasing or decreasing income–environment relationship. Because we set the 'missing' turning point for monotonically decreasing and increasing curves with the mean of relevant turning points, we use the OLS model instead of the tobit model. We choose the OLS model instead of the GLS model and use the robust standard error to deal with the heteroscedasticity problem. In estimating equation (2.2), all the turning points are calculated on the regression coefficients of GDP per capita in the IER in our database, since not all studies display the turning point.[4]

[4] If the turning points are presented in the studies, then we always compare our own calculation with the turning points reported in the studies to make sure that there is no mistake in our calculation. The turning points presented in the primary studies should not differ too much from our calculations, because the difference should be due to the decimal rounding of the regression coefficients that we use to calculate the turning point. If they differ substantially, we try to find the cause and make any necessary adjustment in our database when possible. For example, we find several studies in which the authors forgot to mention the data scale in their studies (e.g. not mentioning whether the GDP per capita value is in thousands). If it is not because of the data scale, if the study has more than one IER, we check whether the same problem occurs in the other IERs. If it does not, then there might be a typing error in the turning point of that IER. We keep that particular IER and use our own turning point calculation. However, if we cannot find the cause of the difference, then we exclude it from our

The regression coefficients are also used to calculate the slope of the IER curves. There are various types of IER. Some of them do not have a turning point (monotonically increasing or decreasing curves), some of them have either a maximum turning point or a minimum turning point (U-shaped or inverted U-shaped curves) and others have both turning points (N-shaped curves or inverted N-shaped curves). Therefore, in estimating equation (2.2), we decide to differentiate the turning points into maximum and minimum turning points, and then we study the effect of the explanatory variables on the location of each turning point (as captured by the GDP per capita level). Hence, there are two estimation models for equation (2.2) in our study, while the previous studies only estimated one type of turning point (see Table 2.1). The other difference between our study and the earlier studies is that we employ the maximum turning point from the environmentally friendly curves, which consist of three types of curves, specifically monotonically decreasing, inverted U-shaped and inverted N-shaped, while, in the former research, the maximum turning point from the inverted N-shaped curve was not considered.

Table 2.2 presents the descriptive statistics of the dependent variables. These statistics shows more variation in the maximum turning point than in the minimum turning point.

Table 2.2 – Dependent Variables

Code	Definition	Number of Observations	Mean (St. Deviation)
SHAPE	• The IER is a monotonically increasing curve (*SHAPE* = 1)	392	
	• The IER is an N-shaped curve (*SHAPE* = 2)	38	
	• The IER is a U-shaped curve (*SHAPE* = 3)	74	
	• The IER is an inverted-U shape (*SHAPE* = 4)	316	
	• The IER is an inverted-N shape (*SHAPE* = 5)	20	
	• The IER is a monotonically decreasing curve (*SHAPE* = 6)	79	
TP_{max}	Maximum turning point (GDP per capita in constant 2000 US$) for the environmentally friendly curves		22,062 (22,428)
TP_{min}	Minimum turning point (GDP per capita in constant 2000 US$) for the environmentally deteriorating curves		16,278 (10,820)

For each turning point, we determine whether it lies within the range of GDP per capita in our database. If the turning point of an IER is beyond the range of GDP per

database. We also draw the IER graph to check the IER shape and determine whether a turning point is a maximum turning point or a minimum turning point.

capita in the sample of our database, we examine the shape of the IER within the range of GDP per capita to define it. For example, if the maximum turning point of an inverted U-shaped IER is below the minimum range of GDP per capita so that, within the range of GDP per capita, the curve is monotonically decreasing, then we consider the IER as a monotonically decreasing curve. If the maximum turning point of an inverted N-shaped IER is above the maximum range of GDP per capita while, within the range of GDP per capita, the curve has a U shape, then we define no maximum turning point in the meta-database. If the maximum turning point of an inverted U-shaped IER is above the maximum range of GDP per capita while, within the range of GDP per capita, the curve is monotonically increasing, then we define the IER as a monotonically increasing curve.

To obtain the range of GDP per capita in our database, first we define the earliest and latest years within our database, viz. 1830 and 2011. Then, we employ the GDP per capita in constant 2000 US$ for the period 1960–2011 from the World Development Indicators of April 2013 (World Bank, 2015) and the GDP per capita in constant 1990 international GK$ for the period 1830–1959 from Angus Maddison (Groningen University, 2015) to find the minimum and maximum GDP per capita values during the period 1830–2011 after changing them into GDP per capita in constant 2000 US$. The range of GDP per capita in our database is from US$55 to US$108,111.[5]

A monotonically decreasing curve within the range of GDP per capita is treated as if it has a maximum turning point. On the other hand, a monotonically increasing curve is considered as if it has a minimum turning point. Because the monotonically decreasing and monotonically increasing IERs in fact have no turning point, we need to set a dummy turning point for those curves. The dummy turning points are taken from the mean of the relevant turning points in the range of GDP per capita of the samples in the studies in our database. The method used to define the relevant turning points is explained further below. This technique is different from the method used in the previous studies (see Table 2.1).Finally, as stated before, for monotonically decreasing and increasing IERs within the range of GDP per capita, we replace the turning point with the mean value of the relevant turning points, that is, the turning

[5] Since the work on this chapter was carried out, an update of the Maddison data has become available which could prevent us from mixing data from different sources. We leave this for future work.

points within the range of GDP per capita of the samples in the studies in our database. There are several steps in obtaining this mean value of the relevant turning point. First, we determine the range of GDP per capita of the sample in our database, as we will further explain below. Since the distribution of the turning point within the range of GDP per capita is skewed to the right (see Figure 2.2), indicating that large extreme values exist, in the next step, we identify the relevant turning point. Based on the histogram and curve of cumulative percentage of the turning point in Figure 2.1, we conclude that the relevant turning point values are around US$4,000 and US$36,000 per capita, which contain about 50% of the total data (see the cumulative distribution in Figure 2.2). We calculate the mean value of the turning points on the basis of these relevant values (see Table 2.3).

Figure 2.2 – **Histogram with a Normal Curve (above) and a Curve of Cumulative Distribution (below) of the Turning Points within the GDP per Capita Range**

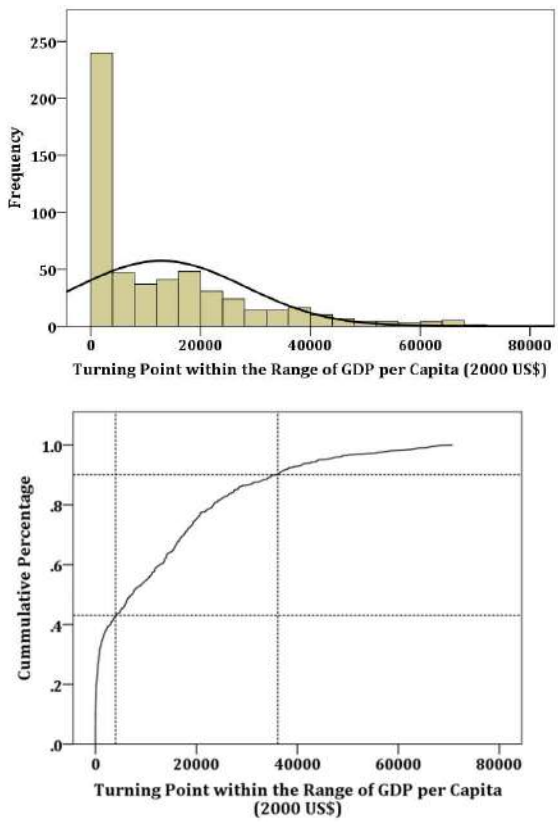


Table 2.3 – **Summary of Relevant Turning Points in the Range of GDP per Capita**

Mean	Standard Deviation	Skewness	Minimum	Maximum	N
16,612.69	8,158.67	0.44	3,982.70	36,127.77	268

2.3.2 Data

To identify the studies that are the basis of our meta-database, we employ Google Scholar and subscription journals to collect articles for the database. The keywords that we use to find the papers are income–emission relationship (IER), Environmental Kuznets Curve (EKC), and CO_2 emissions. We restrict the period of the articles to 1991–2014. The starting year 1991 is chosen because it is the time when the first EKC study was published (Grossman & Krueger, 1992). Based on this first selection, we identify 1,167 potentially relevant articles. Next, we select articles that estimated CO_2 emissions using GDP or GDP per capita as an income indicator and that were published in a journal or a book. Based on this selection, we are left with 209 articles. We do not include working papers. We use the ranking from the Scimago Journal & Country Rank (SJR, 2007) to measure the journal quality, but we allow estimates derived from papers in journals that are less prominent, that is, those that have no ranking in the SJR, to be included in the sample with a zero ranking.

Subsequently, we carefully identify all the explanatory variables in the EKC studies in our database and then group them into one variable if they have similar characteristics. For example, studies that included globalization, trade openness, integration into the international market, the KOF index of globalization, exports, imports, dirty exports or dirty imports in their model as explanatory variables are defined as studies that use a *TRADE* variable.

Several considerations are involved in choosing the variables that are included as controls in the estimation. First, we include variables that were included in previous studies (Li et al., 2007; Card et al., 2010; Koirala et al., 2011; Goldman, 2012), except for pollutant variables (because we focus only on CO_2), and the goodness of fit of the model. We do not include the latter variable, because, in our database, many studies did not display the coefficient of determination (R^2). Using the goodness of fit as an explanatory variable would thus substantially reduce the number of observations available to estimate the meta-regression model. Therefore, we decide to exclude it from the model. Second, we exclude the explanatory variables that cause collinearity problems. For example, we do not include variables that indicate whether a study used time series data or panel data, because they have high correlations. For three models with three different dependent variables, if we include all the types of data (cross-sectional, time series and panel) in the model, then STATA, the software that we use, will always omit one of them. This leaves us with 26 variables (see Table 2.4). The explanatory variables in the ordinal logistic model and the ordinary least square model are the same.

Table 2.4 – Explanatory Variables

	Variable	Description	Mean	Standard Deviation
Study Quality	*PUBLISH*	If the study was published by a prominent journal/publisher,[(1)] then *PUBLISH* = 1, else *PUBLISH* = 0	0.95	0.22
	YEARPUB	Year of publication	2,008.92	4.62
	RANK	SJR ranking	1.44	0.95
Type of Data	*CROSSSEC*	If the study used cross-sectional data, then *CROSSSEC* = 1, else *CROSSSEC* = 0	0.06	0.24
	SAMPLE	Sample size in the study[(3)]	808.58	1,160.87
	PERIOD	Span of the time period covered	36.30	29.67
	YEARDATA	Year of data used in the study for cross-section data and median year of time period covered otherwise	1,977.01	114.14
	DEVELOP	If the study included only developed countries in the sample, then *DEVELOP* = 1, else *DEVELOP* = 0	0.30	0.46
	UNDEV	If the study included merely less developed countries in the sample, then *UNDEV* = 1, else *UNDEV* = 0	0.26	0.44
	MULTI	If the study used multi-country data, then *MULTI* = 1, else *MULTI* = 0	0.72	0.45
Method	*FIXED*	If the study used the fixed-effect method, then *FIXED* = 1, else *FIXED* = 0	0.30	0.46
	RANDOM	If the study used the random-effect method, then *RANDOM* = 1, else *RANDOM* = 0	0.12	0.33
	ROBUST	If there are procedures or tests that signal that the analysis is of good quality, e.g. the unit root test, heteroscedasticity, the Hausman test, etc., then *ROBUST* = 1, else *ROBUST* = 0	0.77	0.42
Control Variables	*TREND*	If the study included a time trend, then *TREND* = 1, else *TREND* = 0	0.07	0.25
	POPULATION	If the study employed population or population density as an explanatory variable, then *POPULATION* = 1, else *POPULATION* = 0	0.09	0.29
	DEMOGRAPHY	If the study employed data related to demography (e.g. GNI index, education, HDI, household characteristics, dependence ratio, working force and urbanization) as an explanatory variable, then *DEMOGRAPHY* = 1, else *DEMOGRAPHY* = 0	0.09	0.29
	TRADE	If the study employed trade proxies, e.g. international trade, exports, imports, dirty exports and dirty imports, as an explanatory variable, then *TRADE* = 1, else *TRADE* = 0	0.15	0.36

Table 2.4 – Explanatory Variables (continued)

	Variable	Description	Mean	Standard Deviation
Control Variables	*ECOACT*	If the study employed economic activities (i.e. output, economic share or value added, employment, etc.) in industry, manufacturing, services, agriculture and tourism sectors or areas used for agriculture as an explanatory variable, then *ECOACT* = 1, else *ECOACT* = 0	0.19	0.40
	ENERGY	If the study employed energy proxies (e.g. energy consumption, energy intensity, imports of energy, clean energy, dirty energy and electricity) as an explanatory variable, then *ENERGY* = 1, else *ENERGY* = 0	0.29	0.46
	FINANCE	If the study employed financial data (e.g. external debt, foreign direct investment (FDI), gross capital formation, financial development, financial liberalization, inflation rate, etc.) as an explanatory variable, then *FINANCE* = 1, else *FINANCE* = 0	0.04	0.19
	ENVIPOL	If the study employed environmental policies (i.e. investment in the environment, the Clean Development Mechanism project, the Kyoto Protocol and environmental regulation) as an explanatory variable, then *ENVIPOL* = 1, else *ENVIPOL* = 0	0.04	0.20
	RESTECH	If the study employed factors related to research and technology (e.g. research intensity, technology gap, technology change, the ARCO index, CO_2 intensity, internet usage, etc.) as an explanatory variable, then *RESTECH* = 1, else *RESTECH2* = 0	0.05	0.21
	GOVPOL	If the study employed factors related to governance and politics (e.g. democracy, political freedom, government expenditure, bureaucracy, corruption, rule of law, political stability, military development, etc.) as an explanatory variable, then *GOVPOL* = 1, else *GOVPOL* = 0	0.06	0.24
	TRANSPORT	If the study employed factors related to transportation (i.e. length of the road network, transportation, and utility) as an explanatory variable, then *TRANSPORT* = 1, else *TRANSPORT* = 0	0.01	0.11
	ENVIRONMENT	If the study employed environmental factors (i.e. land area, forest area, temperature, weather and climate) as an explanatory variable, then *ENVIRONMENT* = 1, else *ENVIRONMENT* = 0	0.03	0.17
	SPATIAL	If the study employed spatial spillover as an explanatory variable, then *SPATIAL* = 1, else *SPATIAL* = 0	0.01	0.11

Notes: (1) A prominent journal/publisher is one that had a ranking in the Scimago Journal & Country Rank (SJR) in 2013. SJR is an open portal that presents journal rankings measuring a journal's impact, influence or prestige (SJR, 2007). (2) The rank of a study in the SJR. If a study comes from a journal/publisher that has no rank in the SJR, then RANK = 0. (3) If the sample size is not available in a paper, it is assumed to equal the number of countries times the length of the data period. (4) Because of the multicollinearity problem, variables indicating whether a study used time series data and variables indicating whether a study used panel data are excluded from the model. (5) The dummy *MULTI* is not equal to the sum of the cross-section and panel-data dummy because some observations are based on state or province data. (6) The number of observations for all the variables is 919.

To make sure that all the data are comparable, we change the CO_2 emissions data into metric tons (MT) and convert the income values into constant US$ of 2000, which were mostly used in the papers, using the formula below:

$$\frac{TP \text{ from a study}}{\text{(constant in 2000)}} = \frac{TP \text{ from a study}}{\text{(constant in year Z)}} \times \frac{GDPcap \text{ (constant in 2000) in year Z}}{\text{Current } GDPcap \text{ in year Z}} \tag{2.3}$$

with *GDPcap* being *GDP* per capita. The GDP per capita values that are used to transform the *TP* are taken from the World Development Indicators (World Bank, 2015), the Penn World Table (Groningen University, 2015) and the Maddison Project Database (GGDC, 2015).

In addition, we count the percentage of the positive slope of IER curves at different development stages (as captured by the GDP per capita) to investigate whether there is an indication in general that the EKC theory can be proved. Therefore, we convert all the slopes into elasticity values $\left(\frac{\partial \ln CO_2cap}{\partial \ln GDPcap}\right)$, where CO_2cap is CO_2 emissions per capita, because most papers used CO_2 emissions per capita and GDP per capita in logarithm values as the indicators for emissions and income. For example, when the original IER is not in a natural logarithm:

$$CO_2cap = constant + a \cdot GDPcap + b \cdot (GDPcap)^2 \tag{2.4}$$

then the slope of equation (2.4), that is $\left(\frac{\partial CO_2cap}{\partial GDPcap}\right) = a + 2b \cdot GDPcap$, is transformed using the formula below:

$$\left(\frac{\partial \ln CO_2cap}{\partial \ln GDPcap}\right) = \left(\frac{\partial CO_2cap}{\partial GDPcap}\right) \times \frac{GDPcap}{CO_2cap} \tag{2.5}$$

with CO_2cap taken from equation (2.4). We calculate the slope values at predefined points of GDP per capita, that is, at the minimum and maximum ranges of GDP per capita in the sample and at the minimum, mean and maximum of the relevant turning point. Furthermore, we calculate the fraction of positive slopes of IER curves at those points. If the fraction of positive slopes of IER curves is decreasing as the GDP per capita is increasing, it indicates that the EKC theory works. Any estimates from studies that could not be converted into a common and comparable metric are excluded from the database. Finally, we are left with 136 articles that give us 919 estimated income-emission relationships. Coding of the database was done by Sotya Fevriera in close cooperation with Henri de Groot and Piet Rietveld, who in the initial phase provided inputs on the coding schemes to be used and the structure of the meta-database to be constructed, and in later stages checked versions of the database for consistent coding and provided inputs on aspects where choices in coding had to be made.

2.4 Results and Discussion

The results of our meta-regression analyses are displayed in Tables 2.5–2.7.

Explaining the Shape of the Curve

Table 2.5 shows the odds ratio and the marginal effect of the estimation of the model specified in equation (2.1), where SHAPE is the dependent variable. In addition, at the right-hand side of the table, we compare the results of our study with those of foregoing studies in terms of the sign effect. The results presented in Table 2.5 show that the journal ranking, the utilization of data only from developed countries and the usage of variables related to trade and the environment significantly increase the probability of obtaining an environmentally friendly curve in the primary studies. In contrast, studies published by a prominent journal/publisher, using a relatively large sample size or long data period and control variables related to demography, energy, and governance and politics significantly reduce the possibility of obtaining an environmentally friendly curve. In addition, the utilization of cross-sectional data and multi-country data has no significant effect on the shape of the IER curve.

More precisely, holding the continuous variables at their mean values and the dummy variables at one, an increase in the SJR ranking by 1 point[6] increases the likelihood of obtaining a monotonically decreasing curve by 3.8%, an inverted-N curve by 0.09% and an inverted-U curve by 0.88%. The SJR measures the number of citations received by a journal and the importance or prestige of the source of citation journals (SJR, 2007). Thus, the higher the number of citations and/or the more prestigious the source of the citation journal, the higher the tendency for a study on the IER to find an environmentally friendly curve.

[6] The range of the SJR rank in our database is 0.100–5.175. If the paper is unpublished, then we set a score of 0.

Table 2.5 – Results of the OLR Model and Comparison with Previous Studies

Variable	Odds Ratio	Marginal Effect for *SHAPE* Category						A	B	C
		1	2	3	4	5	6			
PUBLISH	0.239 ***	0.282 ***	0.019 **	0.029 *	−0.129 ***	−0.031 **	−0.170 *			+ ***
	(0.003)	(0.000)	(0.026)	(0.081)	(0.000)	(0.016)	(0.053)			
YEARPUB	1.016	−0.004	−8.0e-5	2.3e-5	0.003	2.6e-4	0.001			
	(0.505)	(0.506)	(0.506)	(0.713)	(0.508)	(0.505)	(0.501)			
RANK	1.729 ***	−0.133 ***	−0.003 **	0.001	0.088 ***	0.009 ***	0.038 ***			
	(0.000)	(0.000)	(0.013)	(0.632)	(0.000)	(0.000)	(0.000)			
CROSSEC	1.018	−0.004	−9.7e-5	2.1e-5	0.003	3.1e-4	0.001			
	(0.971)	(0.971)	(0.972)	(0.958)	(0.971)	(0.971)	(0.971)			
SAMPLE	1.000 **	0.000 **	8.5e-7 *	−2.4e-7	−2.7e-5 **	−2.8e-6 **	−1.2e-5 **	+ ***	− ***	−
	(0.028)	(0.028)	(0.081)	(0.641)	(0.029)	(0.050)	(0.031)			
PERIOD	0.990 ***	0.002 ***	5.1e-5 **	−1.5e-5	−0.002 ***	−1.6e-4 **	−0.001 ***	+ ***	+	+ **
	(0.004)	(0.004)	(0.046)	(0.636)	(0.005)	(0.013)	(0.006)			
YEAR DATA	0.999	0.000	3.1e-6	−8.9e-7	−9.7e-5	−10e-6	−4.2e-5			
	(0.400)	(0.400)	(0.416)	(0.679)	(0.401)	(0.403)	(0.401)			
DEVELOP	1.722 **	−0.129 **	−0.004 *	−0.002	0.083 **	0.010 **	0.042 **	−	+ **	+ ***
	(0.020)	(0.016)	(0.096)	(0.482)	(0.013)	(0.049)	(0.040)			
UNDEV	1.098	−0.023	−0.001	4.7e-5	0.015	0.002	0.007			
	(0.674)	(0.673)	(0.699)	(0.877)	(0.672)	(0.678)	(0.680)			
MULTI	1.010	−0.003	−5.2e-5	1.6e-5	0.002	1.7e-4	0.001	− *	+ **	−
	(0.963)	(0.963)	(0.963)	(0.966)	(0.963)	(0.963)	(0.963)			
FIXED	1.067	−0.016	−3.5e-4	5.9e-5	0.010	0.001	0.005			
	(0.767)	(0.766)	(0.779)	(0.781)	(0.766)	(0.769)	(0.768)			
RANDOM	1.204	0.045	−0.001	−2.9e-4	0.029	0.003	0.014			
	(0.499)	(0.492)	(0.583)	(0.832)	(0.489)	(0.514)	(0.521)			
ROBUST	0.763	0.065	0.002	4.4e-4	−0.042	−0.005	−0.020			
	(0.209)	(0.201)	(0.337)	(0.753)	(0.195)	(0.237)	(0.246)			
TREND	1.353	−0.072	−0.002	−0.001	0.046	0.005	0.024	− **		
	(0.332)	(0.316)	(0.471)	(0.692)	(0.303)	(0.386)	(0.380)			
POPULATION	1.356	−0.072	−0.002	−0.001	0.047	0.005	0.024	−	−	
	(0.428)	(0.413)	(0.549)	(0.748)	(0.397)	(0.472)	(0.479)			

Table 2.5 – Results of the OLR Model and Comparison with Previous Studies (continued)

Variable	Odds Ratio	Marginal Effect for *SHAPE* Category						A	B	C
		1	2	3	4	5	6			
DEMOGRAPHY	0.265 ***	0.317 ***	−0.008	−0.026 **	−0.207 ***	−0.015 ***	−0.060 ***	− ***	+	
	(0.001)	(0.000)	(0.204)	(0.043)	(0.000)	(0.000)	(0.000)			
TRADE	1.408 *	−0.081 *	−0.003	−0.001	0.053 *	0.006	0.026	− **	−	
	(0.087)	(0.078)	(0.209)	(0.545)	(0.068)	(0.133)	(0.133)			
ECOACT	0.968	0.008	1.6e-4	−6.1e-5	0.005	0.001	−0.002	+ ***		
	(0.910)	(0.910)	(0.906)	(0.926)	(0.910)	(0.910)	(0.909)			
ENERGY	0.712 *	0.083 *	0.001 *	−0.002	−0.055 *	−0.005	−0.022 *			
	(0.078)	(0.079)	(0.081)	(0.381)	(0.081)	(0.103)	(0.062)			
FINANCE	1.367	−0.074	−0.003	−0.001	0.048	0.006	0.025			
	(0.476)	(0.459)	(0.599)	(0.764)	(0.441)	(0.527)	(0.526)			
ENVIPOL	0.880	0.031	4.9e-4	−0.001	−0.021	−0.002	−0.008			
	(0.721)	(0.723)	(0.598)	(0.831)	(0.724)	(0.713)	(0.708)			
RESTECH	0.445	0.200 *	−0.002	−0.013	−0.132 *	−0.010 **	−0.042 **			
	(0.104)	(0.092)	(0.666)	(0.360)	(0.088)	(0.037)	(0.024)			
GOVPOL	0.544 *	0.151 *	−4.7e-4	−0.007	−0.100 *	−0.008 **	−0.034 **			
	(0.089)	(0.086)	(0.859)	(0.363)	(0.085)	(0.046)	(0.033)			
TRANSPORT	0.468	0.188	−0.002	−0.012	−0.124	−0.010	−0.039 *			
	(0.197)	(0.182)	(0.714)	(0.451)	(0.173)	(0.106)	(0.078)			
ENVIRONMENT	4.186 **	−0.277 ***	−0.020 **	−0.030	0.122 ***	0.032 **	0.174 *			
	(0.011)	(0.000)	(0.046)	(0.115)	(0.000)	(0.027)	(0.090)			
SPATIAL	0.876	0.033	4.9e-4	−0.001	−0.022	−0.002	−0.009			
	(0.813)	(0.815)	(0.706)	(0.887)	(0.816)	(0.806)	(0.803)			
CUT 1: 28.540		CUT 2: 28.721		CUT 3: 29.072		CUT 4: 31.112			CUT 5: 31.370	
N	919									
Wald chi²	92.570 ***									
Pseudo R^2	0.039									

Notes: (1) Values in the bracket are the p-value. The robust standard errors are not displayed. (2) *, ** and *** refer to significant at 10%, 5% and 1% level for one-sided hypothesis. (3) A = result from Li et al. (2007), B = result from Koirala et al. (2011), C = result from Goldman (2012). The results of Li et al. (2007), Koirala et al. (2011) and Goldman (2012) are based on the multinomial logistic model with three shape categories (see Table 2.1). We only display the results for category 1 (in comparison with category 3 which is the base category). (4) In Koirala et al. (2011), PUBLISH refers to a published journal article. In Goldman (2012) YEARPUB refers to number of years since publication date.

The utilization of data merely from developed countries increases the probability of obtaining a monotonically decreasing curve by 4.2%, an inverted-N curve by 1% and an inverted-U curve by 8.3%. However, the usage of data only from less developed countries does not have a statistically significant influence on the shape of the IER curve. The use of trade as a control variable increases the tendency to find an inverted-U shape by 5.3%. The biggest contribution comes from control variables related to the environment, which could improve the chance of gaining a monotonically decreasing curve by 17.4%, an inverted-N curve by 3.2% and an inverted-U curve by 12.2%.

Our result on the impact of using data from developed countries only supports the results from Koirala et al. (2011) and Goldman (2012), but the positive significant effect of trade in our study contrasts the negative significant effect of trade reported by Li et al. (2007). The first potential reason for this difference in sign is that we focus our analysis on CO_2 emissions, while the previous studies considered all types of pollution. A characteristic of CO_2 emissions is that, as a global pollutant, they cross borders, while some other pollutants in the previous studies are local pollutants. The share of CO_2 emissions in previous studies is relatively smaller than that of other pollutants.[7] When the negative effect of a pollutant is global, then there will be a force from people in other areas to encourage people who live around the source of the pollution to put more effort into reducing it. Moreover, according to the theory of North–South trade,[8] the North (developed) countries might try to move some of its manufacturing production to Southern (less developed) countries (Rowthorn & Kenneth, 2013). It becomes a way for dirty industries in 'green havens' (strict environmental policy countries) to continue their activities in 'pollution havens' (less stringent environmental policy countries) (Poelhekke & van der Ploeg, 2015) or the practice of 'ecological dumping' (Rauscher, 1992). This creates trade between the North and the South and drives a structural change in the North from industry to the service sector and in the South from agriculture to the industry sector, which is often used to explain the EKC theory. Trade might not relate directly to some pollutants in

[7] A total of 19% of studies in Cavlovic et al. (2000) and 34.17% of observations in Koirala et al. (2011) used CO_2 as an indicator for pollution, while 28.4% of studies in Li et al. (2007) used anthropogenic activity as an indicator for pollution. Hence, the cases that used CO_2 in Li et al. (2007) must be less than 28.4%.

[8] A similar explanation of the theory of North–South trade is often discussed through the displacement hypothesis, pollution haven hypothesis and race-to-the-bottom scenario (Dinda, 2004).

previous studies. This might be the other reason for the different sign for trade between our study and previous studies.

As noted, Table 2.5 also shows that the likelihood of a study reporting an environmentally friendly curve is reduced when it is published by a prominent journal/publisher, uses a relatively large sample size or long data period and uses control variables related to demography, energy, and governance and politics. More precisely, a study that is published in a prominent journal/by a prominent publisher significantly diminishes the likelihood of obtaining a monotonically decreasing curve by 17%, an inverted-N curve by 3.1% and an inverted-U curve by 12.9%. This finding contrasts with Goldman's (2012) finding and shows that a prominent journal/publisher tends to find an environmentally deteriorating curve, indicating that an article from a prominent journal/publisher tends to be more stringent in its assessment of environment analysis quality.

Furthermore, our results imply that enlarging the sample size by 100 observations and increasing the range of the data period by 1 year consecutively only decreases the possibility of finding a monotonically decreasing curve by 0.12% and 0.1%, an inverted-N curve by 0.028% and 0.016% and an inverted-U curve by 0.27% and 0.2%. The first finding supports the result from Koirala et al. (2011) but contrasts with the result from Li et al. (2007), whereas the finding on the length of the data period contrasts with the results from Li et al. (2007) and Goldman (2012).

Including a control variable related to energy decreases the probability of a study obtaining a monotonically decreasing curve by 2.2% and an inverted-U curve by 5.5%. A study that contains a control variable related to governance and politics has a lower possibility of obtaining a monotonically decreasing curve by 3.4%, an inverted-N curve by 0.8% and an inverted-U curve by 10%. A study incorporating a control variable related to demographic issues that is not related to the population reduces the likelihood of obtaining a monotonically decreasing curve by 6%, an inverted-N curve by 1.5% and an inverted-U curve by 20.7%. The last finding supports Li et al. (2007).

Variables related to financial data does not have significant effect on the probability of finding environmentally friendly IER curve. Among our EKC studies sample that the employ financial data, studies with FDI have the highest frequency. According to Demena & Afesorgbor (2019), a meta-analysis using EKC studies with

FDI but without considering its heterogeneity will result an insignificant effect. However, this study does not consider the heterogeneity in the variable related to financial or FDI data because some observations that used those various indicators has limited frequency so if they are defined as a variable, it won't have enough variations.

Finally, we find high correlations between the utilization of cross-sectional data, multi-country data, time series data and panel data. Among those four variables, Cavlovic et al. (2000) only employed cross-sectional data while Li et al. (2007), Koirala et al. (2011) and Goldman (2012) used panel data and multi-country data. Therefore, we only include cross-sectional data and multi-country data in the model. Our study shows that the usage of both cross-sectional and multi-country data has no significant effect on the tendency to find an environmentally friendly curve. Goldman (2012) also found that multi-country data have no significant effect on the likelihood of obtaining an environmentally friendly curve, but Li et al. (2007) concluded that they have a negative significant effect while Koirala et al. (2011) found that they have a significant positive effect. Thus, there is a possibility that the likelihood of obtaining an environmentally friendly curve increases with the usage of time series or panel data. However, the utilization of panel data was found to have a significant but negative effect by Li et al. (2007) and a not significant effect by Koirala et al. (2011) and Goldman (2012).

Explaining the Turning Points of the Curve

Table 2.6 presents the estimation results for equation (2.2), explaining the maximum and minimum turning points of the EKC curve. Again, the right-hand side of the table compares the results of our study with those of foregoing studies in terms of the sign effect. In Table 2.6, a negative effect of an explanatory variable on the maximum turning point shows the impact of that explanatory variable on the decrease in the maximum turning point, implying that environmental improvement (a decrease in pollution) starts at a lower level of per capita income (an earlier development phase). In contrast, a negative effect of an explanatory variable on the minimum turning point shows the impact of that explanatory variable on the decrease in the minimum turning point, implying that environmental degradation (an increase in pollution) starts at a lower level of per capita income (an earlier development phase).

Table 2.6 – Results of the OLS Models and Comparison with Previous Studies for TP_{max}

lnTP_{min}	Variable	TP_{max}	Cavlovic et al. (2000)	Li et al. (2007)	Koirala et al. (2011)
−0.4209 * (0.0808)	PUBLISH	1.6e+04 *** (0.0002)			+
−0.0415 *** (0.0031)	YEARPUB	605.8338 (0.1470)			
0.1140 (0.1021)	RANK	−2.9e+03 ** (0.0439)			
−0.1509 (0.4068)	CROSSSEC	4,988.5300 (0.5028)	+ and –		
0.1950 ** (0.0156)	lnSAMPLE	2,436.2200 *** (0.0035)	+ ***	+ **	+ **
0.0041 (0.1515)	PERIOD	19.4123 (0.6432)		+ *	– **
0.0007 *** (0.0002)	YEARDATA	4.7564 (0.3057)			
−0.4626 ** (0.0122)	DEVELOP	−1.1e+03 (0.7614)	– ***	+ **	–
−0.7866 *** (0.0001)	UNDEV	−1.6e+03 (0.7234)			
−1.1416 *** (0.0002)	MULTI	5,260.9100 * (0.0921)			+ **
0.2975 ** (0.0272)	FIXED	−7.1e+03 * (0.0621)			
−0.0891 (0.6611)	RANDOM	−5.0e+03 (0.3859)	+ and –		
−0.2592 ** (0.0466)	ROBUST	−755.9840 (0.7760)		+	
−0.0229 (0.9045)	TREND	−1.4e+04 *** (0.0000)		+	
0.0405 (0.8053)	POPULATION	−3.8e+04 *** (0.0000)	–	+ **	– **
1.1369 *** (0.0000)	DEMOGRAPHY	3,445.7300 (0.5308)	+	+	–
0.3226 ** (0.0318)	TRADE	1,601.5100 (0.5308)	+ ***	–	+ and –
−0.0774 (0.6384)	ECOACT	1.4e+04 *** (0.5974)	– **	– ***	
−0.6688 *** (0.0000)	ENERGY	−1.5e+04 *** (0.0000)			
0.1594 (0.4312)	FINANCE	5,240.7400 (0.2538)			
0.4643 ** (0.1269)	ENVIPOL	−9.5e+04 (0.1452)			
0.1859 (0.5639)	RESTECH	1.3e+04 * (0.0592)			
0.5453 *** (0.0003)	GOVPOL	1.3e+04 *** (0.0025)			
0.2021 (0.2821)	TRANSPORT	3.4e+04 *** (0.0080)			
−0.1257 (0.4324)	ENVIRONMENT	3.0e+04 *** (0.0016)			
0.5051 ** (0.0417)	SPATIAL	1.1e+04 *** (0.0248)			
91.7370 *** (0.0011)	CONSTANT	−1.2e+06 (0.1436)	+ ***	+ ***	+ ***
501	N	415			
4.51 ***	F	63.94 ***			
0.2352	R^2 adjusted	0.3003			

Notes: (1) The values in the bracket are p-values. The robust standard errors are not displayed, (2) *, ** and *** refer to significance at the 10%, 5% and 1% level for a one-sided hypothesis, (3) ln refers to natural logarithm, (4) In our study, PUBLISH means that a study was published in a prominent journal or by a prominent publisher, while, in Koirala et al. (2011), PUBLISH means a published journal article.

In short, the results presented in Table 2.6 show that studies published by a journal/publisher with a higher ranking and using a fixed-effect model, a time trend, population and data related to energy as control variables significantly lower the predicted maximum turning point. In contrast, a reputable journal/publisher, a larger sample size and the usage of multi-country data all have a significant positive effect on the predicted maximum turning point.

The finding that studies published by a higher-ranked journal/publisher tend to lower the maximum turning point shows that a study with a more careful analysis is likely to lead to lower maximum turning points. A higher-ranked journal/publisher is likely to be a prestigious journal/publisher, and this usually implies more stringent control of the quality of the analysis. According to Cavlovic et al. (2000), the finding that a fixed-effect model tends to produce lower turning points than a random-effect model can be explained by the fact that the greater variability in the regression coefficients in the random-effect model might yield a higher turning point. In a fixed-effect model, countries or regions have the same regression coefficients but different constants. In a random-effect model, each country or region has specific regression coefficients and constants.

Our result that the inclusion of a time trend as well as the population size and energy lowers the maximum turning point may successively be explained by the effect of technology, population density and development on the maximum turning points. In primary studies, a time trend has usually been included as an indicator for technological progress (De Groot, 1999). If technological progress is energy saving, it may well decrease the emission levels per capita, thus fostering the achievement of the turning point. As regards the role of population size, in general, it correlates with population density. According to the compact city theory (Dieleman & Wegener, 2004; Mindali et al., 2004; Neuman, 2005), a higher population density could bring efficiency into energy usage and reduce the environmental degradation. Finally, energy is needed for development and should have a high correlation with income. According to the EKC theory, a sufficiently high income could drive people to put more effort into having a better environment by buying energy-efficient appliances.

As noted, we also find that a reputable journal/publisher, the sample size and the usage of multi-country data have a positive significant effect on the predicted maximum turning point, implying that environmental improvement (a decrease in pollution) starts at a higher level of per capita income. A study that comes from a recognized journal/publisher might utilize a bigger sample size with more countries and/or a longer period in the database. A study from a recognized journal/publisher, with a bigger sample size and multi-country data, has a greater chance of using a sample containing developing and/or underdeveloped countries, which generally reach the turning point later than developed countries. Hence, a reputable journal/publisher, the sample size and the usage of multi-country data could yield higher maximum turning points.

Furthermore, we find that the utilization of data related to economic activities, research and technology, governance and politics, transportation, the environment and spatial spill-over as control variables has a positive significant effect on the estimated maximum turning point. Most studies that used data related to economic activities employed the share of, or value added from, the manufacturing or industrial sector as an indicator for economic activity. The utilization of data related to economic activity actually describes the structural change, which could have a positive effect on the maximum turning point.

Data related to research and technology are included because development in research and technology could reduce emissions (Ang, 2009). However, research and technology development may take a long time and could even fail, especially when a country does not develop its own technology but adopts it from another country (Sasmojo, 2004). Therefore, research and technology might yield a higher maximum turning point. Data related to good governance and politics measure the implementation of policies on the environment and the law enforcement in the environmental sector (Tamazian & Rao, 2010; Anshasy & Katsaiti, 2014). If there is not enough support from the policies and law enforcement to improve the environment, then the effect of both variables on the maximum turning point will be positive.

Some studies included data related to transportation, such as the length of the road network and the share of the transportation sector in the GDP (Neumayer, 2004; Squalli, 2014). A better transportation infrastructure could reduce costs and therefore increase income. However, if it is not supported by good public transportation, then it will increase the energy usage and CO_2 emissions. Thus, the usage of data related to transportation explains the effect of the transportation service infrastructure and/or public transportation service, which might have a positive effect on the maximum turning point. Some studies utilized data related to the environment, such as temperature, weather, climate, land area and forest area (Neumayer, 2004; Hercegova & Strielkowski, 2011; Squalli, 2014). Those variables could affect productivity and therefore income. Hence, the usage of those variables could reflect the effect of productivity, which could have a positive effect on the maximum turning point when the indicators of environmental variables demonstrate negative features.

Spatial spillovers are included because the environmental quality of a country might influence other countries through the spatial institutional mechanism (Hosseini & Kaneko, 2013). The spillover could happen through the mechanism of the entry of foreign firms and direct investment in a country, technology adoption by a country and cooperation among countries through an economic community or zone. The maximum turning point will increase if the spatial spillover does not work well.

The positive significant effect of the sample size and the usage of multi-country data on the maximum turning point confirm the findings from all of the previous studies (see Table 2.6). However, in our study, the utilization of economic activities has a positive significant influence on the maximum turning point, whereas Cavlovic et al. (2000) and Li et al. (2007) found that the impact is negatively significant. The characteristic of CO_2 emissions as being less visible than some of the other pollutants in the previous studies might also cause a late response in handling the pollution (Card et al., 2010). These will cause a country to take longer to reach the maximum turning point and could lead it to a higher maximum turning point. This might be the reason why we found that the effect has a different sign from that in previous studies.

We also discover that the span of the data period and the usage of data merely from developed countries as a control variable do not have a significant effect on the maximum turning point. In previous studies, the results of those variables were found to be significant but contrary to one another (see Table 2.6). In our study, factors related to trade have no significant effect, but Cavlovic et al. (2000) found that they have a positive significant effect on the maximum turning point.

Table 2.6 also displays the results for the minimum turning point. The existence of a minimum turning point implies rejection of the EKC hypothesis. Our results show that the predicted minimum turning point is significantly negatively influenced by studies published in a prominent journal/publisher, the year of publication, the usage of data only from developed countries or the utilization of data merely from less developed countries, the usage of multi-country data, the application of methods to ensure the analysis quality and the utilization of factors related to energy as a control variable. In contrast, the population size, year of data used in a study, fixed-effect method and usage of factors related to demography, trade, policy on the environment, governance and politics, and spatial spillover as control variables have a positive significant effect on the predicted minimum turning point.

According to Dinda (2004), CO_2 emissions, which have a long-term global impact or an indirect effect on health, might have monotonically increasing IER curves. Using a relative measurement as an indicator for emissions rather than their absolute level may also result in monotonically increasing or U-shaped IER curves (Dinda, 2004). Moreover, some researchers doubted that the environmental improvement in EKC theory is a permanent phenomenon. It seems to be a rather heroic assumption that pollution can keep on decreasing when an economy continues to grow, as described in the EKC theory, and therefore an IER curve might well be N shaped (Tisdell, 2001; Dinda, 2004). The N shape demonstrates the negative effect of high income on the environment that in the long run cannot be offset by technological advances (Borghesi, 1999). This might be due to the scarcity of resources and the high environmental maintenance cost (Dinda, 2004).

Another plausible explanation for the emission increase is that trade fails to reduce emissions. As explained in the previous paragraph, a production shift in the manufacturing or industry sector from developed to less developed countries will encourage trade between those countries. However, this production must be made by sacrificing the environment quality. When less developed countries become prosperous, it is difficult for them to apply policies to improve their environment quality, because they still need resources for production and it is difficult for them to obtain those resources from other countries (Stern, 2004). This condition will be represented by a curve with an increasing slope. Despite those possible causes, Moomaw & Unruh (1997) thought that the N-shaped IER for CO_2 emissions was due to data aggregation.

Finally, we present in Table 2.7 the fraction of positive slopes of the IER curves at predefined levels of the GDP per capita. The IER may have various shapes.

Therefore, we develop a new but simple method to detect whether, in general, most IER studies support the EKC theory. We estimate the slope of the IERs in our database at some values of the GDP per capita. Then, we calculate the percentage of positive slopes of the IER at those points. Table 2.7 displays the percentage of positive slopes at some points of the GDP per capita.

Table 2.7 – Fraction of Positive Slopes at Predetermined Values of GDP per Capita (2000 US$)

GDP per capita (2000 US$)				
54.51[a]	**3,982.70**[b]	**16,612.69**[c]	**36,127.77**[d]	**108,111.21**[e]
77.69%	83.66%	72.47%	64.27%	59.83%

Notes: [a] minimum range of GDP per capita in the sample; [b] minimum value of the relevant turning point; [c] mean value of the relevant turning point; [d] = maximum value of the relevant turning point; [e] = maximum range of GDP per capita in the sample.

According to the EKC theory, after reaching a certain point of income, the environmental degradation will decrease. From Table 2.7, we can see that the relative frequency of positive slopes clearly shows a pattern of an inverted-U shape because, in the early stage of development, the percentage is increasing, but it becomes smaller as the GDP per capita grows. This finding shows that, in general, the IER for CO_2 emissions seems to support the EKC theory.

2.5 Conclusion

This chapter used meta-analysis as technique to analyze existing empirical evidence on the Environmental Kuznets Curve (EKC), an inverted U-shaped relationship that may exist between pollution and the level of economic development. More specifically, we looked for factors that drive the observed shape of the EKC and its turning point values. In contrast to previous meta-analyses on the EKC, we focused on CO_2 emissions as the main source of global warming, we constructed a relatively large dataset covering substantially more studies, we develop an alternative set of dependent variables and we use different regression techniques.

We found evidence supporting the EKC hypothesis. The percentage of observations with positive slopes of the IER curves in our database is increasing at lower levels of GDP per capita, but decreasing for higher GDP per capita. We can conclude that the method of analysis does not have any influence on the probability of finding a more environmentally-friendly IER curve. The probability of finding evidence in favor of the EKC theory is bigger if we use data only from developed countries and tends to be smaller if we use a large sample size and long time series. The choice of control variables is also important. The probability of finding evidence for a more environmentally-friendly IER curve increases if we use variables related to trade and environment, but it is smaller if we use variables related to demography, energy and governance and politics as control variables. In addition, an article published in a prominent journal or in a journal that has an SJR ranking has lower probability to find a more environmentally-friendly IER compared to an article published in a journal that has no SJR ranking or which has zero value of SJR ranking. However, the higher the SJR ranking of a journal, then the greater the chance of finding a more environmentally-friendly IER. Thus, we can say that a more environmentally-friendly IER tends to be found in a journal that has no SJR ranking or that has high SJR ranking. As regards the turning points of the EKC, we found that low predicted maximum turning point tends to be found on studies published by a journal/publisher with a high rank, studies using a fixed effect model, and studies that use a time trend, population and data related to energy as control variables. A low predicted maximum turning point implies that environmental improvement (decrease of pollution) starts at a lower level of per capita income (an earlier development phase). In contrast, a high predicted maximum turning point delays the turn to environmental improvement (decrease of pollution) to higher levels of income (a later development phase). High predicted maximum turning point tends to be found in a reputable journal/publisher, on studies using a large sample size and multi-country data and on studies that use data related to economic activities, research and technology, governance and politics, transportation, environment and spatial spillover as control variables.

We also identified the factors that may contribute to finding a minimum turning point. The existence of a minimum turning point implies a rejection of the EKC hypothesis. A low predicted minimum turning point tends to be found in studies published in a prominent journal/publisher and in higher year of publication or in recently published journals, in studies that apply methods to improve the quality of the analysis such as unit root tests, tests for heteroscedasticity, Hausman tests, etc., and in studies that use factors related to energy as a control variable. Moreover, our results showed that the predicted minimum turning point is significantly negatively influenced by the usage of data only from developed countries or the utilization of data merely from less developed countries, the usage of multi-country data. Thus, the low predicted minimum turning point can be found in any database of countries. In contrast, a high predicted minimum turning point tends to be found on studies with large sample size using recent data or fixed effect method, and on studies that use the usage of factors related to demography, trade, policy on environment, governance and politics and spatial spillover as control variables.

CHAPTER 3 Cultural Drivers of Income-Emission Relationships across Asian Economies

3.1 Introduction

As countries develop economically, the pollution intensity of their economic activity changes. In the literature, much attention has been devoted to the so-called Environmental Kuznets Curve (EKC): an inverted U-shaped relationship that may exist between the level of pollution (like GHG emissions) and the level of economic development (see Stern, 2017, for a recent overview and Chapter 2 for a meta-analysis of the available evidence). The EKC was named after the Kuznets Curve, which was introduced by Simon Kuznets (1955), who predicted that, as per capita income increases, inequality will first rise and then, at a certain level of per capita income, start to fall. In the early 1990s, Grossman & Krueger (1992) used this hypothesis to test for the relationship between economic development and emissions: they indeed found empirical evidence for an inverted U-shaped pattern in the relationship between various polluting emissions and the per capita gross domestic product (GDP). Prominent explanations for the EKC – as a particular form of an income-emission relationship (IER) – include technological innovation in (emission) pollution control, structural change towards a service-based economy (‘deindustrialization’) and income-driven shifts in preferences and environmental policy (Selden & Song, 1994).

This chapter aims to identify the role of cultural values in a society in determining income-emission relationships (IERs) across a sample of Asian economies. The culture of a society can be defined as a set of information that is equitably owned by all the members of society who embrace that culture and use it as their reference in all of their actions and behaviour (Sasmojo, 2004). Since CO_2 emissions result from human activities, cultural values can be thought of as (implicit) drivers of CO_2 emissions. The inverted U-shaped pattern that characterizes the EKC is also often implicitly assumed to be driven by cultural values through their impact on people’s preferences. The idea is that, in the early phase of economic development, the environmental quality may decline, because people are unwilling to trade consumption for investment to improve the environmental quality. However, at higher income levels, the cultural preferences for substituting consumption for investment to prevent environmental degradation are thought to change gradually. As economies develop, awareness of environmental problems increases, which translates into environmental policies and the increased use of relatively environmentally friendly technologies. In addition, the cultural values of a society play a role in determining its ability in science and technology (Sasmojo, 2004), because the private and public institutions of a country reflect its culture. Often, the identification of a culture is reserved for a society such as a nation (Hofstede, 2001). Hence, in this chapter, we hypothesize that cross-country differences in cultural values can (partly) explain differences in emission intensity across countries. Together with the structural economic changes that accompany economic development, cultural values may explain the non-linear patterns of the IER – such as the EKC – that often appear to exist (Moomaw & Unruh, 1997).

Analyses of the statistical relationship between environmental and cultural variables are scarce in the economic literature. An exception is the study by Park et al. (2007), who analysed the relationship between scores on an Environmental Sustainability Index and 4 dimensions of national culture proposed and measured by Hofstede (1983). For a sample of 43 countries, they found that both 'power distance' and 'masculinity' are significantly negatively related to environmental performance. As an illustration of the important role of cultural variables, they did not find a significant non-linear EKC pattern between income and pollution after controlling for the effect of culture.

In contrast to Park et al., we explain per capita CO_2 emissions rather than using a composite environmental sustainability index. We also enrich the measurement of culture by adding two new cultural variables, following more recent work by Hofstede (2018). Finally, instead of analysing a very heterogeneous sample of countries, we focus our analysis on the most important emerging economies in Asia: Bangladesh, China, India, Indonesia, Malaysia, Myanmar, Pakistan, the Philippines and Thailand. Together these countries comprise almost 50% of the world's population and are responsible for most of the global increase in global greenhouse gas emissions over the last decades (World Bank, 2018).

Our analysis covers the period 1972–2014, which allows the use of a panel data approach. Because the estimated shape of IERs from panel data is often quite sensitive to the degree of heterogeneity within the sample (Vollebergh et al., 2005), we develop a mixed-effect regression model with random effects at the country level. This enables us to assume heterogeneous, country-specific slopes rather than homogeneous slopes across, admittedly, a set of diverse countries. In addition to per capita income, population size and technological progress, we control for the potential impact of the use of renewable resources in the energy system, fuel energy prices and the degree of urbanization in our analysis. We distinguish between two specifications of our regression model, explaining per capita CO_2 emissions and per capita CO_2 emissions corrected for the income effect, respectively.[9] In our empirical approach, we first examine the extent to which the observed IER patterns can be explained by variation in per capita income, population size and technological progress. Second, we identify the role of cultural values in society to explain the cross-country variation in IERs over time.

We find that CO_2 emissions' intensity is positively affected by the per capita income and population size, whereas technological progress significantly reduces CO_2 emissions' intensity. We do not find evidence for the existence of an EKC across the countries in our sample; rather, we find an increasing non-linear relationship between per capita income and per capita CO_2 emissions. As regards the role of culture, we find that cultural variables significantly influence the CO_2 emission intensity. When corrected for income, countries with a high-power distance index, a high uncertainty avoidance index, a high individualism (versus collectivism) index and a high long-term (versus short-term) orientation index tend to have lower CO_2 emission intensity. Without income correction, societies with a high masculinity (versus femininity) index and a high indulgence (versus restraint) index are also likely to have lower CO_2 emission intensity.

The structure of this chapter is as follows. In section 3.2, we briefly discuss the dominant theories that have been put forward in the literature to explain the existence of an EKC, with a focus on the Asian context. In section 3.3, we propose a series of hypotheses concerning why cultural values may help in explaining the

[9] See the Appendix for a third specification that explains CO_2 emissions per unit of GDP.

variation in IERs across countries. Section 3.4 presents our data and methodology. In section 3.5, we establish the IER patterns for each country in our sample and identify the role of per capita income, population size and technological progress in explaining these patterns. In section 3.6, we analyse cultural values as potential determinants of IERs. Section 3.7 concludes.

3.2 IER: The Role of Population, Income and Technology

In the existing literature, various theories have been proposed to explain the existence of the Environmental Kuznets Curve (EKC). The first explanation is the occurrence of structural economic change. In the early phase of economic development, industrialization arises, resulting in transition from the agricultural to the industrial sector and causing a positive relationship between pollution and economic development. Later, at higher levels of development, deindustrialization sets in, resulting in the service sector continuing to grow, increasingly at the expense of the industrial sector, which tends to give rise to a negative relationship between pollution and economic development (Moomaw & Unruh, 1997; De Groot, 1999).

Another set of explanations for the existence of an inverted U-shaped relationship between economic development and emissions is concerned with technological change and innovation, which enable the production of more output with less pollution through 'pollution-saving[10] and pollution-using[11] inventions' (De Groot, 1999; Smulders et al., 2011). Smulders et al. (2011) proposed four stages of clean technology diffusion. In the first stage (the 'green phase'), the technology options are few, so pollution prevention tends to be ignored. In the second stage (the 'confidence phase'), more new technology options become available and are implemented. In the third stage (the 'alarm phase'), awareness of the dangerous effects of the new technologies arises. This awareness results in inventions of clean technology in the last stage (the 'cleaning-up phase'). Accounting for the role of technological change in empirical EKC models requires the inclusion of not only per capita income levels but also time trends, which are assumed to capture the dominant trends in technological change (De Groot, 1999). For example, Martinez-Zarzoso and

[10] Technology change that improves fuel efficiency and/or reduces pollution.
[11] Technology change without considering pollution prevention.

Maruotti (2011) and Melenberg et al. (2011) found that time has a negative effect on CO_2 emissions, although it cannot fully compensate for the positive effect of income (Melenberg et al., 2011).

Obviously, population growth is closely related to a country's emission growth. Ceteris paribus, a larger population increases the aggregate energy use, which in turn increases the aggregate greenhouse gas emissions. Therefore, in our models, we include population size as one of the variables that are expected to explain the observed emission patterns. Other variables that influence CO_2 emissions and CO_2 emission intensity may exist, such as the energy price, which has often been neglected in estimates of the IER relationship (Agras & Chapman, 1999). Agras and Chapman (1999) and Fevriera et al. (2013) are exceptions to this and indeed found that the energy price significantly reduces the CO_2 emissions, as is expected, since a higher energy price should reduce the energy demand and associated CO_2 emissions through substitution effects.

Urbanization may also have a positive impact on CO_2 emissions (Abouie-Mehrizi et al., 2012; Jafari et al., 2012; Poumanyvong et al., 2012) for several reasons. First, it could enlarge the energy consumption for transportation. Although the growth of polycentric urban regions could reduce this consumption, the consumption may become less efficient when public transportation is of poor quality and private transportation is supported by a good transportation infrastructure between urban regions (Burgalassi, 2010). Second, urbanization encourages infrastructure improvement to support transportation and the life of new residents in rural areas. The latter usually involves sacrificing some green areas, which reduces the ability of the environment to absorb the emissions (Abouie-Mehrizi et al., 2012).

Wilonoyudho (2011) argued that urbanization could be a lifestyle and is not a result of industrialization. However, Martinez-Zarzoso & Maruotti (2011) stated that both industrialization and urbanization are needed in developing countries to develop their economies further. They found that the relationship between urbanization and CO_2 emissions features an inverted U curve in low-, middle-low- and upper-middle-income countries. Poumanyvong et al. (2012) also found that urbanization has a positive effect on transport energy use, with the largest and smallest impacts experienced by, respectively, high- and middle-income countries, whilst the impact in low-income countries is between those two groups. Although we can conclude that, in general, urbanization increases CO_2 emissions, the inverted-U relationship between urbanization and CO_2 emissions indicates that, in the long run, the benefits of urbanization could overcome the negative impacts (Martinez-Zarzoso & Maruotti, 2011). Excessive urbanization could develop the service (Wilonoyudho, 2010) and informal sectors (Wilonoyudho, 2011). Based on data for 18 OECD countries, Mulder et al. (2014) found evidence that, although the shift towards a service economy contributes to greater energy use, it also contributes to lower energy intensity. For 1995–2005, the average annual growth rate of energy use and energy intensity of the service sector in those countries was 2.3% and –0.6%, respectively.

3.3 IER: The Role of Cultural Values

As noted before, the level and change of environmental awareness in a society are often an important determinant of IERs, since they may be the driver of environmental policies and regulations and the adoption of relatively environmentally friendly technologies (De Groot 1999; Smulders et al., 2011). To measure cultural values, in this chapter, we make use of data from the Hofstede Insights (2018) dataset. This dataset includes six indices to capture six dimensions of a country's set of dominant cultural values: the power distance index, the individualism versus collectivism index, the masculinity versus femininity index, the uncertainty avoidance index, the long-term versus short-term orientation index and the indulgence versus restraint index.[12]

Power distance is a measure of human disparity that could appear in the form of reputation, riches and authority. Different societies attach different values to those dimensions (Hofstede, 2001). The power distance index measures the degree of power inequality in a country. Hofstede Insights (2018) defined power distance as 'the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally'**.** High power distance societies (countries) allow a hierarchical order, while low power distance societies always try to equalize the power distribution (Hofstede Centre, 2014).

[12] In the previous version of Hofstede's study, there is a cultural dimension called pragmatic versus normative, which is different from the score with respect to the long-term versus short-term orientation. Later, he dropped the pragmatic versus normative score and replaced it with the long-term versus short-term orientation (Hofstede Insights, 2018).

Inequality, autocratic governments, frequent corruption and income inequality are characteristics of countries with a high-power distance index (Hofstede, 2011).

Power distance has a negative significant correlation with latitude. Technology in countries with a warmer climate (lower latitude) cannot develop as well as in countries with a colder climate (higher latitude), because there is less need for technology for survival in tropical countries (Hofstede, 2001). Thus, we hypothesize that the power distance index has a positive effect on the CO_2 emission intensity, since low power distance countries have a higher chance of developing technology to reduce their CO_2 emissions. Park et al. (2007), who used a positive indicator for the environment, indeed found that the power distance index has a negative significant effect on the environmental sustainability index.[13]

The individualism versus collectivism index is related to the norms in a society that describe the relationships between individuals and collectivity. Hofstede Insights (2018) defined this index as 'the degree of interdependence a society maintains among its members'. Low-individualism societies often view science and technology as supernatural things, whilst high-individualism societies think of them as factual matters. Hence, high-individualism societies tend to pay more attention to information (Hofstede, 2001). Information is also one way to reduce uncertainty in the future. Hence, we hypothesize that high-individualism societies perform better in developing technologies for CO_2 emission reduction; thus, we expect that the individualism versus collectivism index should have a negative effect on the CO_2 emission intensity. Park et al. (2007) indeed found that the individualism versus collectivism index has a positive significant effect on the environmental sustainability index.

The masculinity versus femininity index refers to the role of men, compared with that of women, in a society. According to Hofstede Insights (2018), this index measures 'what motivates people, wanting to be the best (Masculine) or liking what you do (Feminine)'. Masculine countries (with a high masculinity index) have greater appreciation of accomplishment, valour, boldness and prizes for high achievement, while feminine countries (with a low masculinity index) have high tolerance of collaboration, humility, concern for the helpless and a high living standard (Hofstede

[13] The negative effect in Park et al. (2007) is compatible with the positive effect in our hypothesis.

Centre, 2014). Because feminine countries tend to prefer high broadly defined living standards, their need for a good environment should be higher, so the masculinity versus femininity index should have a positive effect on the CO_2 emission intensity.

Furthermore, masculine countries tend to develop well in the manufacturing sector, particularly on a large scale, such as the manufacturing of large and weighty instruments and 'bulk chemistry', whereas feminine countries tend to develop better in the service sector, such as giving advice and providing transport, producing specific products for customers and managing issues like high production in farming and the chemical processes of living organisms (Hofstede, 2001). Thus, masculine countries should have higher CO_2 emissions and the masculinity versus femininity index should have a positive effect on CO_2 emissions. Park et al. (2007) indeed found that the masculinity versus femininity index has a negative significant effect on the environmental sustainability index.

The uncertainty avoidance index is defined as the degree to which insecurity concerning the future disturbs a society (Hofstede Centre, 2014). Hofstede Insights (2018) measured this index as 'the extent to which the members of a culture feel threatened by ambiguous or unknown situations and have created beliefs and institutions that try to avoid these'. Societies with weak uncertainty avoidance tend to experience less stress and anxiety, are undisturbed by ambiguity and dislike rules, while societies with high uncertainty avoidance worry easily and therefore tend to suffer more from stress, look for clarity and are likely to be more obedient to regulations (Hofstede, 2011). Hence, societies with a low uncertainty avoidance index demonstrate a slower reaction to urgency, whereas societies with a high uncertainty avoidance index always try to seek answers that require analytical thinking, which in turn develops science and technology (Hofstede, 2001). CO_2 emissions change the climate, and climate change brings uncertainty for the future. Technology is one way to cope with the uncertainty in the future. Hence, countries with a high uncertainty avoidance index should perform better in developing technologies to reduce the CO_2 emission intensity and the uncertainty avoidance index should have a negative effect on the CO_2 emission intensity. Park et al. (2007) found that the uncertainty avoidance index indeed has a positive effect on the environmental sustainability index.

Hofstede Insights (2018) described the long-term versus short-term orientation index as '*how every society has to maintain some links with its own past* *while dealing with the challenges of the present and future*'. Countries with a long-term orientation are prosperous countries or countries with high economic growth, whereas countries with short-term orientation are poor countries or countries with slow economic growth (Hofstede, 2011). A long-term-oriented society looks for virtues because of its concern for the future, while a short-term-oriented society is concerned with virtues regarding the past and the present time. Therefore, long-term-oriented societies have a high regard for school, thrift and perseverance, whereas short-term-oriented societies have a high regard for tradition, spending money on community activities and social interaction (Hofstede, 2001). The characteristics of long-term-oriented societies that are concerned with the future could have a relationship with the characteristics of the uncertainty avoidance index, since both have concerns regarding the future. The characteristics of long-term-oriented societies that place a high value on school might reflect their high regard for information, similar to the characteristics of a high-individualism society.

Moreover, societies with strong pragmatism do not need explanations for everything, because, for pragmatists, life is too complex and they choose to live virtuously (Hofstede, 2001). People with this value would perhaps choose to adapt their life to respond to the negative impact of the emissions and would not put too much effort into mitigating it. The characteristic of long-term-oriented societies that a have high value for thrift demonstrates the view of a high-pragmatism society to live virtuously. Thus, societies with a long-term orientation tend to be pragmatic, while societies with a short-term orientation tend to be normative (Hofstede Insights, 2018), and the long-term (pragmatic) versus short-term (normative) orientation index should have a negative effect on CO_2 emissions and on the CO_2 emission intensity.

Hofstede Insights (2018) defined the indulgence versus restraint index as 'the extent to which people try to control their desires and impulse'. Societies in countries with indulgence characteristics tolerate people having basic and natural needs for pleasure in their life, whilst societies in countries with restraint characteristics repress and control those needs with stringent societal norms (Hofstede Centre, 2014). Some forms of enjoying life and having fun might be related to consumption, which will lead to energy utilization. Countries with indulgence characteristics tend to have a higher birth rate when most of their residents are educated and are likely to have more people with obesity than countries with restraint characteristics (Hofstede, 2011). Hence, the indulgence versus restraint index should have a positive effect on CO_2 emissions. People in countries with restraint characteristics tend to realize that their lives are affected by others (Hofstede, 2011), so they might have greater awareness of the environment and the indulgence versus restraint index should have a positive effect on CO_2 emissions.

3.4 Data and Methodology

3.4.1 Data

Our analysis comprises nine emerging Asian countries – Bangladesh, China, India, Indonesia, Malaysia, Myanmar, Pakistan, the Philippines and Thailand – and the period 1972–2014. This period was chosen because of the availability of consistent energy use and CO_2 emissions data across our sample of countries. The countries were selected based on their role as important emerging economies in Asia in combination with the availability of data during the chosen period, such that a balanced panel could be used in our analysis.[14]

The data on income, population size, CO_2 emissions, clean energy, energy prices and urbanization were taken from the World Development Indicator dataset (World Bank, 2018). Our income measure is the per capita GDP in constant 2010 US$ (gdpcap). The population size (pop) is measured in persons. The CO_2 emissions data (CO_2) consist of emissions from the burning of fossil fuels and cement manufacture and are measured in kilotons (kt).[15] Based on the definition from the World Bank, clean energy is non-carbohydrate energy that does not produce carbon dioxide when generated. It consists of alternative (hydropower, geothermal and solar power, among others) and nuclear energy. Clean energy is determined by the natural resources owned by a country and the ability of that country to apply technology to utilize those resources. We measure clean energy (RenewP) as the percentage of renewable energy consumption in the total final energy consumption; the energy price (PGasoline) is the pump price for gasoline measured in $ per litre; and

[14] Cambodia and Vietnam were dropped because of incomplete data series.
[15] Excluding land use change and forestry.

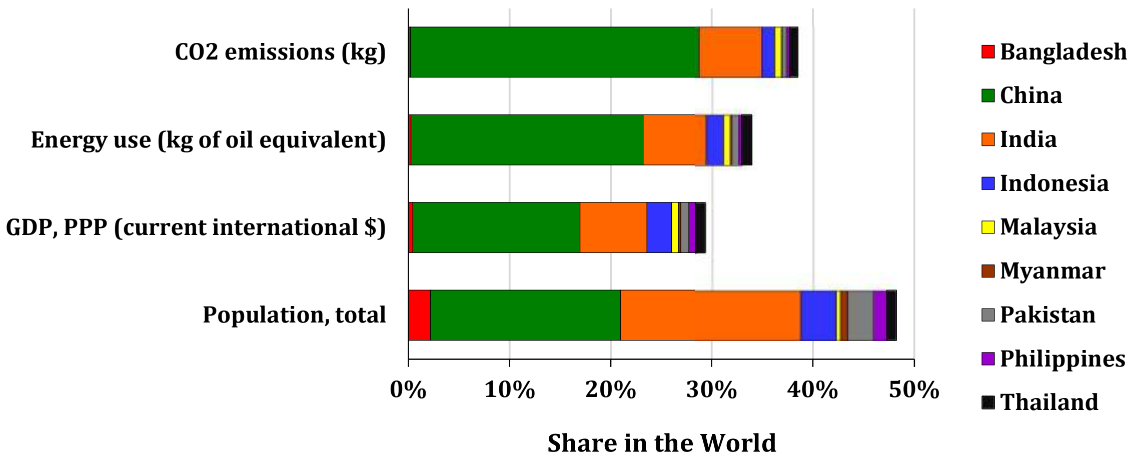
urbanization (UrbanP) is measured in terms of the urban population as a percentage of the total population.

Table 3.1 – Summary Statistics

Variable	Observations	Mean	St. Dev.	Min.	Max.
$lnCO_2pop$	387	−7.098	1.136	−9.866	−4.824
$lnCO_2gdp$	387	−14.128	0.602	−15.627	−12.212
$lnCO_2popEI$	387	−0.257	1.164	−2.958	2.047
$lngdpcap^3$	387	367.906	152.849	133.974	791.297
$lngdpcap^2$	387	50.383	14.025	26.183	85.551
lngdpcap	387	7.030	0.985	5.117	9.249
lnpop	387	18.630	1.310	16.242	21.034
time	387	1993	12.426	1972	2014
PD	344	78.625	13.584	55	100
INV	344	24.25	10.572	14	48
MAS	344	52.625	9.566	34	66
UA	344	49	13.361	30	70
LTO	344	49.625	17.546	27	87
IDU	344	31.5	16.592	0	57
RenewP	225	41.194	22.027	3.819	91.119
PGasoline	94	0.661	0.347	0.12	1.56
UrbanP	387	33.454	12.357	8.221	74.01

Data Source: World Development Indicators (World Bank, 2018) and the Hofstede Insights (2018).

Figure 3.1 – Share of the Emerging Asian Countries for Some Indicators in 2014



Data Source: World Development Indicators (World Bank, 2018)

We take our cultural variables from the Hofstede Insights (2018) dataset. They include the power distance index (PD), the individualism versus collectivism index (INV), the masculinity versus femininity index (MAS), the uncertainty avoidance index (UA), the long-term versus short-term orientation index (LTO) and the indulgence versus restraint index (IDU). The cultural variables are not available for Myanmar. Table 3.1 presents the summary statistics of all the variables in our models and Table 3.2 displays comparison of some indicators of the Asian countries in this study. Table 3.2 shows that although located in the same continent, some Hofstede indicators of those countries variates below and above the midpoint (50).

Table 3.2 – Comparison of Some Indicators of the Important Asian Countries in 2014

Country	Per Capita GDP (PPP)[1]	Energy Intensity[2]	Per Capita Energy[3]	CO_2 Intensity[4]	Cultural indicators[5]					
					PD	INV	MAS	UA	LTO	IDU
Bangladesh	3,131.92	74.75	222.22	2.07	80	20	55	60	47	20
China	13,440.48	175.31	2,236.73	3.37	80	20	66	30	87	24
India	5,672.93	118.37	637.43	2.71	77	48	56	40	51	26
Indonesia	10,537.66	88.36	883.91	2.06	78	14	46	48	62	38
Malaysia	25,487.61	122.65	2,967.54	2.71	100	26	50	36	41	57
Myanmar	5,024.92	77.96	371.87	1.12	-	-	-	-	-	-
Pakistan	4,820.78	105.86	484.45	1.85	55	14	50	70	50	0
Philippines	6,937.85	72.31	476.24	2.22	94	32	64	44	27	42
Thailand	15,651.18	132.57	1,969.63	2.35	64	20	34	64	32	45
World	15,257.44	126.54	1,830.07	2.72						

Notes: [1] GDP per capita, PPP (current international $); [2] energy use (kg of oil equivalent) per $1,000 GDP (constant 2011 PPP); [3] kg of oil equivalent per capita; [4] CO_2 emissions (kg) divided by energy use (kg of oil equivalent); [5] the cultural indicators are abbreviated as follows: PD = the power distance index, INV = the individualism versus collectivism index, MAS = the masculinity versus femininity index, UA = the uncertainty avoidance index, LTO = the long-term versus short-term orientation index and IDU = the indulgence versus restraint index.
Data Source: World Development Indicators (World Bank, 2018) and the Hofstede Insights (2018).

3.4.2 Methodology

Panel data are needed because we want to build a model that can demonstrate how emissions change over time in each country and how they vary among countries. In addition to simplifying the computation and statistical inference, panel data can improve the efficiency of econometric estimates, because they contain more degrees of freedom and sample variability than cross-sectional or time series data (Hsiao, 2007). De Groot et al. (2004) used panel data in their study on IER. They employed a fixed-effect model so that each region in the models has the same slopes (regression coefficients) but individual intercepts. The hump-shaped IER estimated from panel data is quite sensitive to the degree of heterogeneity that characterizes the sample (Vollebergh et al., 2005). Therefore, instead of using homogeneous slopes, we use a model that allows for heterogeneous slopes.

The mixed-effect models with random effects at the country level are specified because random effects allow us to differentiate the intercept and the slopes for each country, which are expected to be important. The models can be written as:

$$y_i = X_i\beta + Z_iu_i + e_i \quad (3.1)$$

with i = 1, …, I where I is the number of countries and t = 1, …, T (covering the period 1972–2014); $y_{i[t,1]}$ is a column vector of T observations for the response variable for each country; $X_{i[t,m]}$ is a matrix of m explanatory variables (the fixed-effect design matrix); $\beta_{[m,1]}$ is a column vector of m coefficients for the explanatory variables (the fixed effects); $Z_{i[t,n]}$ is a matrix of n explanatory variables (the random-effect design matrix); $u_{[n,1]}$ is a column vector of n coefficients for the explanatory variables (the random effects); and $e_{[t,1]}$ is a column vector of errors.

Two models are developed. The dependent variable in the first model is the CO_2 emission intensity measured as CO_2 emissions per capita (in kt) (co_2pop):

$$CO_2pop = \frac{CO_2}{Population} = \frac{CO_2}{GDP} \times \frac{GDP}{Population} \quad (3.2)$$

In the second model, the dependent variable is also the CO_2 emission intensity, but it is corrected for the income effect (CO_2popEI), which is determined through a decomposition analysis:

$$CO_2popEI\ 1972 = CO_2pop\ 1972 \quad (3.3.1)$$

Next, CO_2popEI in the period 1973 to 2014 is defined by the yearly change in CO_2popEI:

$$\Delta CO_2popEI \text{ in } t = \frac{\frac{CO_2 \text{ in year } t}{Population \text{ in year } t} - \frac{CO_2 \text{ in year } t-1}{Population \text{ in year } t-1}}{ln\left(\frac{\frac{CO_2 \text{ in year } t}{Population \text{ in year } t}}{\frac{CO_2 \text{ in year } t-1}{Population \text{ in year } t-1}}\right)} \times ln\left(\frac{\frac{CO_2 \text{ in year } t}{GDP \text{ in year } t}}{\frac{CO_2 \text{ in year } t-1}{GDP \text{ in year } t-1}}\right) \times 100 \quad (3.3.2)$$

with t = 1973–2014.

The explanatory variables come from the population (pop), per capita GDP (constant 2010 US$) and year of data (time). We include population in the models because it affects the energy that is needed to develop. Thus, it can also capture the scale of a country's economy. The latter, *time*, is used to capture the effect of technological progress (or other processes that develop over time and that are not captured by the other explanatory variables in the model). All the variables in the models are in natural logarithms except for time. In the next stage of the analysis, we extend the models by including explanatory variables that come from clean energy, the energy price and urbanization and some cultural variables. We use the models to construct the IER for each of the nine middle-income countries in the sample. The intercept and the slopes for those countries are determined on the basis of the fixed and random effects for the all-countries model.

The maximum likelihood (ML) is a good method to estimate fixed regression parameters. On the other hand, the restricted maximum likelihood (REML) method is better for estimating random variances. The output differences between the two methods are usually small (Field, 2009). The ML method is preferred because it allows different models to be compared.[16]

When the slopes of the model are differentiated for each country, usually the covariance between the intercept and the slopes of the model should not be assumed to be zero (Field, 2009), so first we analyse a model with unstructured covariance. If the correlations between the intercept and the slopes are statistically insignificant, then we may assume zero covariance.

3.5 Results: The IER in Asia

In the basic models, we explain the dependent variables with the per capita real GDP, population and time. The results for the basic models are displayed in Table 3.3 and Table 3.4. In Table 3.3 (Model 1A), the dependent variable is per capita CO_2 emissions.

All the independent variables in Table 3.3 jointly affect the dependent variable at the 1% level of significance. All the standard deviations of the explanatory variables, except for the quadratic of per capita real GDP and time, are statistically significant at the 1% level. The fixed effects of the quadratic effect of per capita GDP and time are constant among countries, because the random effects of these variables are insignificant. In contrast, the fixed effects of the squared effect of GDP per capita

[16] The other consideration in the choice of the ML method is that, in STATA 14.0, which is used to run the method, the command to display robust standard errors is not supported by the REML model.

and population size vary among countries. The negative effect of time indicates that technological progress plays a statistically significant role in reducing CO_2 emissions' intensity in the Asian countries in our sample. This result supports the findings by Martinez-Zarzoso & Maruotti (2011) and Melenberg et al. (2011).

Table 3.3 – Results of the Mixed-Effect Model with per Capita CO_2 Emissions as the Dependent Variable (Basic Model)

Independent Variables	Model 1A – Dependent Variable = $lnco_2pop$								
	All	BGD	CHI	IND	IDN	MYS	MMR	PAK	PHL	THA
Fixed Effects										
lngdpcap3	0.0637 ** (0.0259)	0.0643	0.0645	0.0631	0.0641	0.0629	0.0621	0.0637	0.0630	0.0651
lngdpcap2	−1.3140 ** (0.5520)	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140
lngdpcap	9.7990 ** (3.8834)	9.9189	9.4736	9.7135	9.8782	9.9171	8.7252	8.8296	9.7150	10.0194
lnpop	0.8530 * (0.4385)	1.7858	0.4486	1.3969	1.2343	0.6145	−0.1833	0.9866	0.6862	0.7071
time	−0.0150 ** (0.0068)	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150
cons	−19.4271 (13.5541)	−38.0703	−9.4338	−30.9517	−27.7224	−14.0138	0.2953	−21.7056	−15.0183	−18.2228
Random Effects										
sd(lngdpcap3)	0.0013 *** (0.0005)									
sd(lnpop)	0.5894 *** (0.1607)									
sd(cons)	11.6260 *** (3.0506)									
sd(residual)	0.0921 *** (0.0125)									
Inflection Point	6.8802	6.8123	6.7884	6.9384	6.8280	6.9661	7.0511	6.8709	6.9491	6.7294
Wald Chi²	174.4200 *** (0.0000)									

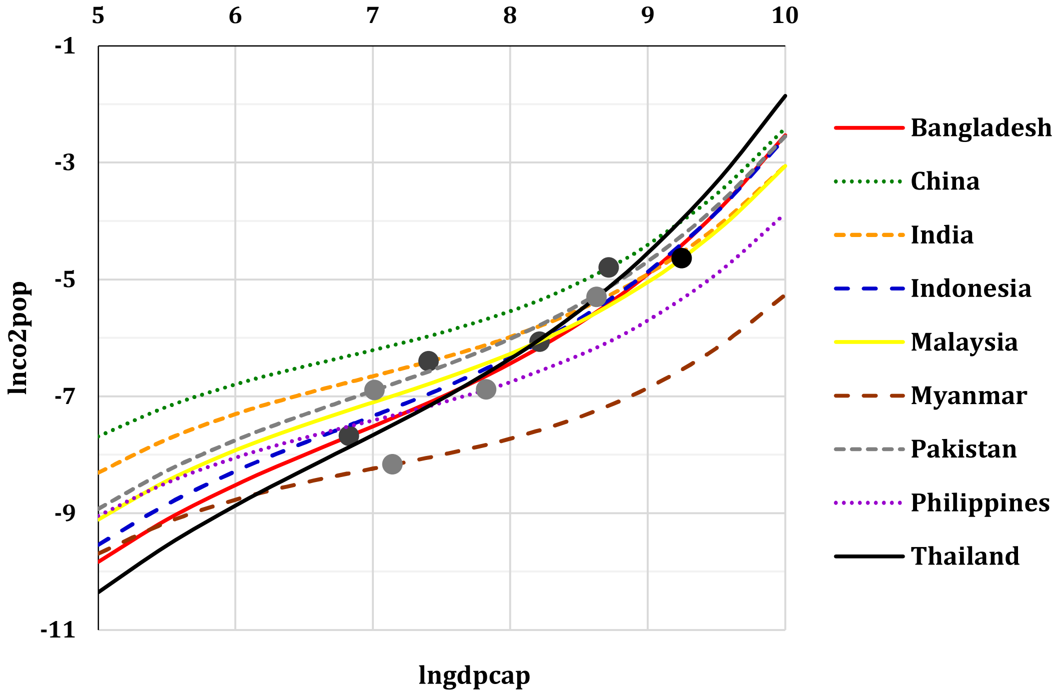
Notes: (1) All = all countries, BGD = Bangladesh, CHI = China, IND = India, IDN = Indonesia, MYS = Malaysia, MMR = Myanmar, PAK = Pakistan, PHL = Philippines, THA = Thailand, (2) ln = natural logarithm. The inflection point of per capita real GDP is calculated in natural logarithm. The curve of this model has no turning point, (3) Values in brackets are robust standard errors, sd = standard deviation, (4) The significance levels at 1%, 5% and 10% are represented by ***, ** and *, respectively, (5) Random effects for lngdpcap2 and time are not presented due to fixed coefficient values among countries, (6) For the Wald Chi², value in the bracket is p-value.

Table 3.4 – Results of the Mixed-Effect Model with per Capita CO_2 Emissions Corrected for the Income Effect as the Dependent Variable (Basic Model)

Independent Variables	Model 2A – Dependent Variable = lnco₂popEI									
	All	BGD	CHI	IND	IDN	MYS	MMR	PAK	PHL	THA
Fixed Effects										
lngdpcap3	0.0540 ** (0.0247)	0.0526	0.0541	0.0538	0.0547	0.0531	0.0536	0.0541	0.0532	0.0566
lngdpcap2	−1.0582 ** (0.5238)	−1.0582	−1.0582	−1.0582	−1.0582	−1.0582	−1.0582	−1.0582	−1.0582	−1.0582
lngdpcap	7.4673 ** (3.6811)	7.3950	7.3959	7.4629	7.4930	7.4911	7.5015	7.4767	7.4466	7.5428
lnpop	1.1807 *** (0.4083)	1.8925	0.9283	1.6808	1.6995	1.0747	0.1097	1.3047	0.8327	1.1034
time	−0.0182 *** (0.0061)	−0.0182	−0.0182	−0.0182	−0.0182	−0.0182	−0.0182	−0.0182	−0.0182	−0.0182
cons	−5.2836 (11.2099)	−18.5051	−0.7234	−17.2298	−15.8679	−0.3273	14.2879	−7.2103	2.3415	−4.3184
Random Effects										
sd(lngdpcap3)	0.0014 *** (0.0005)									
sd(lnpop)	0.5532 *** (0.1409)									
sd(cons)	10.6830 *** (2.4796)									
sd(residual)	0.0940 *** (0.0106)									
Inflection Point	6.5340	6.7116	6.5151	6.5513	6.4500	6.6480	6.5815	6.5168	6.6267	6.2294
Wald Chi²	194.8800 *** (0.0000)									

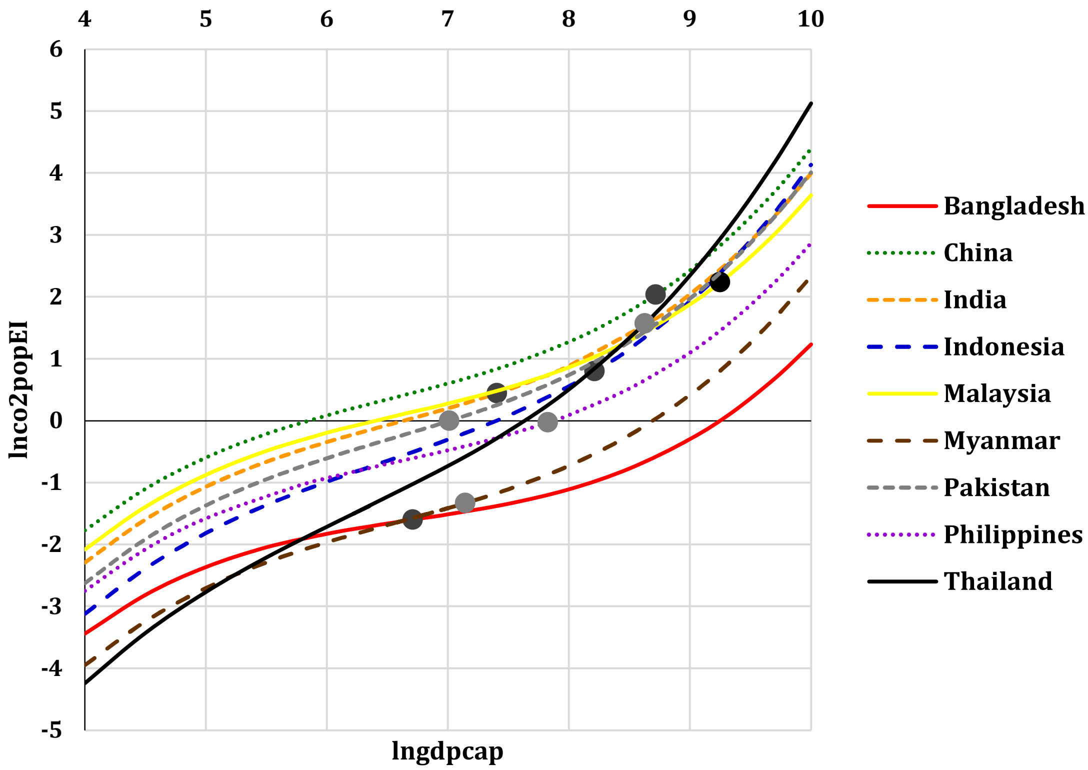
Notes: (1) All = all countries, BGD = Bangladesh, CHI = China, IND = India, IDN = Indonesia, KOR = Korea, Rep., MYS = Malaysia, MMR = Myanmar, PAK = Pakistan, PHL = Philippines, SGP = Singapore, THA = Thailand. (2) ln = natural logarithm. The turning and inflection points of per capita real GDP are calculated in natural logarithms. (3) Values in brackets are robust standard errors, sd = standard deviation. (4) The significance levels at 1%, 5% and 10% are represented by ***, ** and *, respectively. (5) Random effects for lngdpcap2 and time are not presented due to fixed coefficient values among countries. (6) For the Wald Chi^2, value in the bracket is p-value.

Figure 3.2 – Curve Estimation of per Capita CO_2 Emissions in 2014



Notes: (1) The curve estimation is calculated at the level of population in 2014 for various levels of gdpcap. (2) The dot shows the gdpcap of each country in 2014.

Figure 3.3 – Curve Estimation of per Capita CO_2 Emissions Corrected for Income in 2014



Notes: (1) The curve estimation is calculated at the level of population in 2014 for various levels of gdpcap. (2) The dot shows the gdpcap of each country in 2014.

In Figure 3.2, we plot the IER curve based on the coefficient values as obtained from our regression analysis, given the 2014 population size at various levels of per capita real GDP. Because we use random-effect models, we are able to show the cross-country differences in IER patterns. If we were to use a fixed-effect model, then the differences among countries would only be seen in terms of the intercept of the IER curve and the slope of the IER of all the countries would be the same. Figure 3.2 clearly shows that the IER in the Asian economies in our sample does not follow the EKC hypothesis – rather, the IER curves are increasing non-linearly, with a relatively rapid increase in the per capita emission levels at the lowest and highest levels of per capita GDP. The negative significant time trend – a proxy for technological change – cannot suppress the positive effect of per capita income and population growth on per capita emissions. The unproven EKC theory supports the results in Hakim (2011), Saboori et al. (2012), Saboori & Sulaiman (2013), Fevriera et al. (2013)[17] and Tjoek & Wu (2018).

If we replace per capita CO_2 emissions with CO_2 emissions per unit of GDP as the dependent variable, we find very similar effects except for the linear effect of per capita real GDP (see Table 3.6 in the Appendix). The IER curve based on this specification follows an N-shaped pattern (see Figure 3.4 in the Appendix) – again not supporting the EKC hypothesis. If we replace the dependent variable with per capita CO_2 emissions corrected for the income effect (see Model 2A in Table 3.4 and Figure 3.3), most results do not change either, except that, for all the countries, the effect of the population size changes from below one to above one or per capita CO_2 emissions become elastic to the population size. Hence, a population size increase of 1% will increase the per capita CO_2 emissions by more than 1%.

Our results show that all the Asian countries in our sample have passed their inflection point. The inflection point marks the moment when the increase in per capita CO_2 emissions becomes faster as the income grows. For Indonesia, the inflection point in Figure 3.2 is 6.828 (see Table 3.3), which corresponds to a per capita GDP level of $923 (constant 2010 US$). Clearly, Indonesia is now at the stage

[17] Using samples of 105 and 79 countries, Fevriera et al. (2013) found proof for the EKC theory if the dependent variable is CO_2 emissions, but the EKC theory was not proved when the dependent variable is CO_2 emission intensity or CO_2 emissions per energy use.

at which its high economic growth is accompanied by a relatively fast increase in per capita CO_2 emissions.

We find that Bangladesh, China and Thailand reached the inflection point at a lower level of per capita income than Indonesia (see Table 3.3). If the per capita CO_2 emissions are corrected for the income effect, then Thailand is the only country that reached the inflection point at a lower level of per capita income than Indonesia (see Table 3.4).

Next, we use Figure 3.2 and Figure 3.3 to compare the IER between Indonesia and other countries with the population size in 2014 and at various levels of per capita income. In both figures, we also show the level of per capita income of each country in 2014. The countries that had a higher per capita income than Indonesia in 2014 are China, Malaysia and Thailand.

Comparing Indonesia with China, we can see in Figure 3.2 and Figure 3.3 that, at the same level of per capita income, China's per capita CO_2 emissions are higher than those of Indonesia but that Indonesia is catching up with China. When we correct the per capita CO_2 emissions with income, then, at a low level of per capita income, the difference in per capita CO_2 emissions between China and Indonesia in Figure 3.3 becomes smaller than that in Figure 3.2. However, the difference is relatively the same at a high level of per capita income. This indicates that income plays an important role in the difference in energy consumption and CO_2 emissions between China and Indonesia.

If we compare Indonesia with Thailand at the same level of per capita income, then we can see that, at a low level of per capita income, the per capita CO_2 emissions of Thailand are lower than those of Indonesia, but, at a high level of per capita income, they catch up and become higher than those of Indonesia. This indicates that Thailand consumes more energy, allowing it to have a higher per capita income than Indonesia. Nonetheless, the difference in per capita CO_2 emissions between Thailand and Indonesia is relatively the same in Figure 3.2 and Figure 3.3, indicating that income might not have an effect on the difference in energy consumption and CO_2 emissions between Thailand and Indonesia.

Comparing Indonesia with Bangladesh, we can see in both figures that the per capita CO_2 emissions of Indonesia tend to be higher than those of Bangladesh. At a low level of per capita income, the difference in per capita CO_2 emissions in Figure 3.2 and

Figure 3.3 is relatively the same, but, at a high level of per capita income, it becomes zero in Figure 3.2. On the other hand, it increases in Figure 3.3. Thus, income might be the main factor that causes the difference in per capita CO_2 emissions between Bangladesh and Indonesia.

If we compare Indonesia with India and Malaysia at the same level of per capita income, then we can see that, at a low level of per capita income, the per capita CO_2 emissions of India and Malaysia are higher than those of Indonesia, but, at a high level of per capita income, Indonesia's emissions catch up and overtake those of India and Malaysia. This indicates that Indonesia consumes more energy than India and Malaysia. The difference in per capita CO_2 emissions between Indonesia and India and Malaysia in Figure 3.2 only differs slightly from that in Figure 3.3. At a low level of per capita income, the difference in per capita CO_2 emissions between Indonesia and India decreases when we correct the per capita CO_2 emissions with income. On the other hand, the difference in per capita CO_2 emissions between Indonesia and Malaysia increases at a low level of per capita income, indicating that income may make a small contribution to explaining the difference in energy consumption and CO_2 emissions between Indonesia and India and Malaysia, which makes the per capita income of Indonesia in 2014 lower than that of Malaysia but higher than that of India.

Comparing Indonesia with Pakistan, we can see in both figures that, at the same level of per capita income, the per capita CO_2 emissions of Indonesia tend to be higher than those of Pakistan, but the difference becomes zero at a high level of per capita income. The difference in per capita CO_2 emissions between Indonesia and Pakistan in Figure 3.2 is similar to that in Figure 3.3. Hence, income has no impact on the difference in per capita CO_2 emissions between Indonesia and Pakistan.

Comparing Indonesia with the Philippines at the same level of per capita income, we can see that, at a low level of per capita income, the per capita CO_2 emissions of the Philippines are higher than those of Indonesia, but, at a high level of per capita income, Indonesia's emissions catch up and overtake those of the Philippines. This indicates that Indonesia consumes more energy than the Philippines, causing Indonesia to have a higher per capita income than the Philippines. The difference in per capita CO_2 emissions between Indonesia and the Philippines in Figure 3.2 is like that in Figure 3.3. Therefore, it indicates that income has no effect on the difference in energy consumption and CO_2 emissions between Indonesia and the Philippines.

Last, comparing Indonesia with Myanmar, we can see in both figures that, at the same level of per capita income, the per capita CO_2 emissions of Indonesia are higher than those of Myanmar. At a low level of per capita income, the difference in per capita CO_2 emissions between Indonesia and Myanmar in Figure 3.2 is smaller than that in Figure 3.3. At a high level of per capita income, on the other hand, the difference in per capita CO_2 emissions between Indonesia and Myanmar in Figure 3.2 is bigger than that in Figure 3.3. Therefore, the difference in energy consumption and CO_2 emissions between Indonesia and Myanmar is influenced by income.

3.6 Results: The Role of Culture

In Table 3.5 and Table 3.6, we extend the basic model underlying the results presented in Table 3.3 and Table 3.4. In Table 3.5 (Model 1B) and Table 3.6 (Model 2B), the dependent variable is per capita CO_2 emissions and per capita CO_2 emissions corrected for the income effect, successively. In those tables, we do not include the random effect from the independent variables, because it makes the coefficient signs become unstable, so it is difficult to compare the models. Moreover, the countries' cultural data do not vary over time, so the random effects of cultural variables are statistically insignificant.

In Model 1B1 in Table 3.5, in which we add cultural variables, the effects of non-cultural variables are still statistically significant, but the effect of population becomes negative and, on the other hand, the effect of time becomes positive. This suggests that a country's culture could encourage people to use energy more efficiently. Although cultures tend to be constant over time, because people from different countries have different cultures, they have a tendency to act differently regarding energy use. People from one country may tend to use it wisely and people from another country may have a tendency to use it carelessly.

Table 3.5 – Results of the Mixed-Effects Model with per Capita CO_2 Emissions as the Dependent Variable (Extended Model)

Independent Variables	Dependent Variable: $lnCO_2pop$			
	Model 1B1	**Model 1B2**	**Model 1B3**	**Model 1B4**
Fixed Effects				
$lngdpcap^3$	0.0419*** (0.0141)	0.0377 (0.0253)	0.0552*** (0.0131)	0.0502* (0.0264)
$lngdpcap^2$	–0.8538*** (0.3150)	–0.8639 (0.5648)	–1.1990*** (0.2790)	–0.9835 (0.6255)
lngdpcap	5.9742** (2.3290)	6.8776 (4.1872)	8.2397*** (1.8891)	6.0083 (7.2557)
lnpop	–0.8090*** (0.0536)	–0.6369*** (0.1075)	–1.0127*** (0.0491)	–0.0666 (0.2709)
Time	0.0436*** (0.0029)	0.0107** (0.0051)	0.0284*** (0.0021)	–0.0046 (0.0122)
PD	–0.1335*** (0.0040)	–0.0862*** (0.0064)	–0.4249*** (0.0336)	–0.0943 (0.1404)
INV	0.0128* (0.0076)	0.0574*** (0.0131)	0.0866** (0.0374)	–0.0547 (0.0959)
MAS	0.0483*** (0.0076)	0.0455*** (0.0113)	0.4843*** (0.0590)	0.1317 (0.1354)
UA	–0.1038*** (0.0118)	–0.0024 (0.0162)	–0.0665 (0.0790)	–0.2292 (0.1942)
LTO	0.0167** (0.0077)	0.0539*** (0.0119)	0.0772* (0.0447)	–0.0837 (0.1132)
IDU	0.0391*** (0.0061)	0.0455*** (0.0083)	0.3018*** (0.0406)	0.0096 (0.0710)
lngdpcapPD			0.0453*** (0.0047)	0.0090 (0.0178)
lngdpcapINV			0.0025 (0.0052)	0.0060 (0.0148)
lngdpcapMAS			–0.0491*** (0.0080)	–0.0215 (0.0168)
lngdpcapUA			0.0200* (0.0112)	0.0206 (0.0279)
lngdpcapLTO			0.0043 (0.0062)	0.0091 (0.0173)
lngdpcapIDU			–0.0303*** (0.0056)	–0.0066 (0.0100)
RenewP		–0.0160*** (0.0025)		–0.0214*** (0.0034)
PGasoline		–0.0363 (0.0611)		–0.1125** (0.0555)
UrbanP		0.0155*** (0.0034)		0.0021 (0.0068)
Constant	–82.4204*** (7.3172)	–35.8889*** (10.1806)	–75.6999*** (7.8964)	10.2405 (22.6194)
Random Effects				
sd (Residual)	0.1698*** (0.0071)	0.0659*** (0.0081)	0.1127*** (0.0048)	0.0476*** (0.0048)
Wald Chi^2	14883.3100*** (0.0000)	48072.4600*** (0.0000)	28291.0100*** (0.0000)	73938.1400*** (0.0000)

Notes: (1) PD = the power distance index, INV = the individualism versus collectivism index, MAS = the masculinity versus femininity index, UA = the uncertainty avoidance index, LTO = the long-term versus short-term orientation index and IDU = the indulgence versus restraint index, (2) ln = natural logarithm. The turning and inflection points of per capita real GDP are calculated in natural logarithms, (3) The values in brackets are robust standard errors; sd = standard deviation, (4) The significance levels of 1%, 5% and 10% are represented by ***, ** and *, respectively, (5) Random effects are not presented, because all the countries have the same coefficient values. (6) For the Wald Chi^2, the value in the brackets is the p-value.

Table 3.6 – Results of the Mixed-Effects Model with per Capita CO_2 Emissions Corrected for the Income Effect as the Dependent Variable (Extended Model)

Independent Variables	Dependent Variable: $lnCO_2popEI$			
	Model 2B1	Model 2B2	Model 2B3	Model 2B4
Fixed Effects				
lngdpcap³	0.0098 (0.0122)	−0.0330 (0.0250)	0.0377*** (0.0119)	−0.0114 (0.0310)
lngdpcap²	−0.0988 (0.2697)	0.8009 (0.5651)	−0.7806*** (0.2530)	0.4671 (0.7221)
lngdpcap	0.2483 (1.9791)	−5.9317 (4.2135)	12.1853*** (1.7713)	−0.6491 (8.3270)
lnpop	−0.5062*** (0.0450)	−0.5813*** (0.1315)	−0.4186*** (0.0528)	0.0900 (0.3031)
Time	0.0323*** (0.0024)	0.0170*** (0.0060)	0.0179*** (0.0020)	−0.0055 (0.0129)
PD	−0.1275*** (0.0036)	−0.1114*** (0.0083)	−0.2311*** (0.0330)	0.0658 (0.1693)
INV	−0.0306*** (0.0061)	0.0183 (0.0156)	0.0609* (0.0341)	−0.0791 (0.1133)
MAS	0.0061 (0.0065)	0.0182 (0.0135)	0.5212*** (0.0531)	0.0317 (0.1663)
UA	−0.1695*** (0.0094)	−0.0936*** (0.0197)	0.1081 (0.0724)	−0.1401 (0.2346)
LTO	−0.0316*** (0.0063)	0.0075 (0.0144)	0.0577 (0.0403)	−0.0352 (0.1366)
IDU	0.0012 (0.0051)	0.0153 (0.0100)	0.2687*** (0.0369)	0.0059 (0.1146)
lngdpcapPD			0.0169*** (0.0047)	−0.0157 (0.0214)
lngdpcapINV			−0.0111** (0.0048)	−1.2e−5 (0.0170)
lngdpcapMAS			−0.0702*** (0.0072)	−0.0188 (0.0202)
lngdpcapUA			−0.0346*** (0.0106)	−0.0129 (0.0339)
lngdpcapLTO			−0.0116** (0.0056)	−0.0083 (0.0203)
lngdpcapIDU			−0.0389*** (0.0051)	−0.0148 (0.0146)
RenewP		−0.0066** (0.0028)		−0.0156*** (0.0040)
PGasoline		−0.2002*** (0.0605)		−0.1931*** (0.0686)
UrbanP		0.0120*** (0.0033)		0.0063 (0.0083)
Constant	−35.0431 (5.6367)	1.4988 (12.4023)	−72.4775*** (7.4344)	24.8353 (27.7381)
Random Effects				
sd (Residual)	0.1512*** (0.0062)	0.0739*** (0.0065)	0.1060*** (0.0046)	0.0618 (0.0055)
Wald Chi²	21598.4600*** (0.0000)	27426.5600*** (0.0000)	32187.8100*** (0.0000)	40870.6400*** (0.0000)

Notes: (1) PD = the power distance index, INV = the individualism versus collectivism index, MAS = the masculinity versus femininity index, UA = the uncertainty avoidance index, LTO = the long-term versus short-term orientation index and IDU = the indulgence versus restraint index, (2) ln = natural logarithm, (3) The values in brackets are robust standard errors; sd = standard deviation, (4) The significance levels of 1%, 5% and 10% are represented by ***, ** and *, respectively, (5) Random effects are not presented, because all the countries have the same coefficient values, (6) For the Wald Chi², the value in the brackets is the p-value.

More specifically, as regards the role of cultural variables, we find evidence supporting our hypotheses on the masculinity versus femininity index, the uncertainty avoidance index and the indulgence versus restraint index. It appears that countries with a relatively low masculinity versus femininity index, relatively high uncertainty avoidance characteristics and a relatively low indulgence versus restraint index feature relatively low per capita CO_2 emissions. The finding for the masculinity versus femininity index confirms the previous results obtained by Park et al. (2007), while the result for the uncertainty avoidance index reinforces those attained by Fevriera et al. (2013).

Our hypothesis that the power distance index has a positive effect on CO_2 emissions is not proved. We found that the effect of power distance index is negative. However, the effect is significant. Therefore, countries with a higher power distance index should have a greater chance of improving technology to reduce CO_2 emissions. The better technological progress in countries with a higher power distance index may be because, in those countries, people with higher authority could have greater power to encourage technology development or law enforcement on the environment.

Our hypotheses for the individualism versus collectivism index and the long-term versus short-term orientation index are not proved, despite the effects being significant. However, when correcting the per capita CO_2 emissions with income (see Model 2B1 in Table 3.6), the negative effects of the individualism versus collectivism index and the long-term versus short-term orientation index are proved. The result for the individualism versus collectivism index supports the finding by Park et al. (2007).

In Model 1B2 in Table 3.5, we present evidence that the use of clean energy can significantly reduce the per capita CO_2 emissions. This finding for clean energy confirms the result reported by Fevriera et al. (2013). In contrast, urbanization significantly increases the per capita CO_2 emissions. The finding for urbanization strengthens the results presented by Martinez-Zarsoso & Maruotti (2011) and Poumanyvong (2012) but, on the other hand, weakens the finding by Glaeser & Kahn (2010), which might be because Glaeser & Kahn used data from cities in the United States that proved the compact city theory in the Western world. However, this theory has not been proved in developing countries. In Chapter 5, we discuss our finding that the compact city theory is not proved in Indonesia. The positive effect of urbanization on CO_2 emissions in Indonesia might be because structural change caused by industrialization arises from agriculture and moves into the industry sector and because the service sector, which could decrease the emissions, is still developing. Moreover, the effect of the energy price is negative but insignificant. Hence, an increase in the energy price appears to have no statistically significant effect on reducing per capita CO_2 emissions; this is probably due to a relatively inelastic demand for energy, given that energy is needed to support many activities in human life. However, adding clean energy, urbanization and the energy price makes the effects of income and the uncertainty avoidance index become insignificant. When a society has a high uncertainty avoidance index, it will probably try to increase its usage of clean energy and its per capita CO_2 emissions, so the effect of clean energy is negative. The reduction of per capita CO_2 emissions then makes the monotonically increasing IER also no longer significant.

In Model 1B3 in Table 3.5, the interaction effects between the per capita income and the power distance index, the masculinity versus femininity index, the uncertainty avoidance index and the indulgence versus restraint index are statistically significant, with the sign effects being the opposite to the sign of the individual cultural effects. Hence, if the per capita income is constant, then the effect of those cultural variables can be positive or negative, depending on the magnitude of the per capita income.

If we include clean energy, urbanization, the energy price and the interactions between per capita income and cultural variables (see Model 1B4 in Table 3.5), the coefficient signs of several variables become unstable and most variables become statistically insignificant. Adding the interactions between per capita income and culture could cause the price effect to be significant and, in contrast, make the urbanization effect insignificant. Including clean energy, urbanization, the energy price and the interactions between per capita income and cultural variables also makes the quadratic and linear effects of income and the population effect become insignificant. It turns the effect of technology negative, although it becomes insignificant. Therefore, those variables could encourage the development of technology to reduce CO_2 emissions. However, the effect is insignificant. Adding those variables also changes the significance and/or the sign effects of cultural variables. In

Model 2B1 in Table 3.6, we present the results for our model, which is similar to Model 1B1 in Table 3.5 except that we correct the dependent variable, that is, per capita CO_2 emissions, for the income effect. As we have stated before, this changes the sign effects for the individualism versus collectivity index and for the long-term versus short-term orientation, thus proving our hypotheses that individualism versus the collectivity index and long-term versus short-term orientation have a negative effect on the CO_2 emission intensity. Correcting the per capita CO_2 emissions with the income effect also causes the negative effect of the energy price to become significant. This finding supports the results obtained by Agras & Chapman (1999) and Fevriera et al. (2013).

Including variables of clean energy, the energy price, urbanization and/or the interactions between per capita income and cultural variables makes the sign effects of some variables unstable. Adding the interactions between per capita income and cultural variables makes the income effects become significant or the shape of the IER curve significantly monotonically increasing. Including clean energy, the energy price and urbanization changes the sign effects of income. Thus, clean energy, the energy price and urbanization could change the shape of the IER curve from monotonically increasing to monotonically decreasing, although the income effects are insignificant. Together, clean energy, the energy price, urbanization and the interactions between per capita income and cultural variables also change the sign and the significance effects of population and technology. The effect of population becomes positive, while the effect of technology becomes negative. However, both effects become insignificant.

Adding the interactions between per capita income and cultural variables also changes the sign and the significance effects of several cultural variables. Including clean energy, the energy price and urbanization changes the sign and significance effects of the individual versus collectivity index and the long-term versus short-term orientation index. Thus, if a society has a high long-term orientation index, it might have a tendency to buy energy with lower CO_2 emissions despite the high price. Nevertheless, if the energy price is already high, then a society with a high long-term orientation index might choose to buy cheaper energy that produces more CO_2 emissions. Together, clean energy, the energy price, urbanization and the interactions between per capita income and cultural variables could also change the sign and/or the significance effects of some cultural variables.

In the previous sections, by comparing the IER curves, we explained that income might have no effect or only a small effect on the difference in per capita CO_2 emissions between Indonesia and Thailand, Malaysia, India, Pakistan and the Philippines. The lower growth of per capita CO_2 emissions in Indonesia compared with Thailand and the higher growth of per capita CO_2 emissions of Indonesia compared with India, Malaysia, Pakistan and the Philippines might be due to differences in the values of cultural dimensions.

Because our hypothesis for the power distance index is not proved, that is, the effect of power distance index is not positive but significantly negative, therefore, in countries with a higher power distance index, the higher power of authority might be able to force the law on the environment to reduce the per capita CO_2 emissions. Indonesia's power distance index is higher than that of Thailand, but its power distance index is lower than those of Malaysia and the Philippines.

If the per capita CO_2 emissions are corrected with income, then our hypothesis for the individualism versus collectivism index is proved. Societies with a high individualism characteristic have a tendency to pay more attention to information (Hofstede, 2001), which is needed to cope with future uncertainty, like the mitigation of climate change caused by CO_2 emissions. This attitude could drive the development of technology that can bring efficiency to energy usage or decrease the CO_2 emissions per income, which is a component of per capita CO_2 emissions. Indonesia has a lower individualism versus collectivism index than India, Malaysia and the Philippines.

Countries with a high masculinity index have a tendency to achieve better development in the manufacturing sector (Hofstede, 2001), which can cause high CO_2 emissions per income. On the other hand, countries with a high femininity index or a low masculinity index tend to develop well in the service sector (Hofstede, 2001). Societies with a high feminine characteristic like to have a high living standard (Hofstede Centre, 2014), so they might demand a good environment, such as low CO_2 emissions. Indonesia has a lower masculinity versus femininity index than Thailand.

People with high uncertainty avoidance tend to be more stringent on regulation (Hofstede, 2011), including environmental law enforcement. People with high uncertainty avoidance will react quickly to matters of urgency (Hofstede, 2001), such as climate change, and tend to develop science and technology well (Hofstede, 2001), which will enable them to develop better technology for energy efficiency that can decrease CO_2 emissions per income. Indonesia's uncertainty index is lower than that of Pakistan.

Our hypothesis for the long-term versus short-term orientation index is proved if per capita CO_2 emissions are corrected with income. Countries with a long-term orientation tend to be more prosperous (Hofstede, 2011). People with a long-term orientation have a high concern for education (Hofstede, 2001). This characteristic will lead them to develop science and technology well and enable them to develop technology to save the energy usage and enable the reduction of CO_2 emissions per income. People with a long-term orientation also choose to live virtuously and hence have a high regard for thrift (Hofstede, 2001). People with these characteristics might have high awareness of the environment and might well have a lifestyle that helps in saving the environment, for example by using vehicles or electrical appliances that are environmentally friendly. Indonesia has a higher long-term versus short-term orientation index than Thailand.

Societies with a low indulgence versus restraint index tend to control their desires and impulses, so they only consume things to fulfil their basic and natural needs to enjoy pleasures in their life (Hofstede Centre, 2014). This characteristic will help in preserving the environment from degradation, saving energy and reducing CO_2 emissions. Indonesia's indulgence versus restraint index is lower than that of Thailand but higher than that of India and Pakistan.

3.7 Conclusion

This chapter developed a mixed-effect regression model with random effects at the country level to identify the role of cultural values in determining income–emission relationships (IER) across a sample of Asian economies over the period 1972–2014. Our sample included the most important emerging economies in Asia: Bangladesh, China, India, Indonesia, Malaysia, Myanmar, Pakistan, the Philippines and Thailand. In addition to per capita income, population size and technological progress, we controlled in our analysis for the potential impact of the use of renewable resources in the energy system, fuel energy prices and the degree of urbanization.

We found that the per capita income has a significant positive effect on the CO_2 emission intensity. We also found that the technological progress in the emerging

Asian countries significantly reduces CO_2 emissions' intensity, whereas the population size significantly increases per capita CO_2 emissions' intensity. Despite the fact that technological change, captured by a time trend, tends to decrease CO_2 emissions' intensity, our results reject the existence of an EKC in the countries of our sample. Rather, we found an increasing non-linear relation between per capita income and CO_2 emission intensity. Furthermore, we found evidence that the CO_2 emission intensity can be reduced through greater usage of clean energy but is likely to increase with continued urbanization.

As regards the role of culture, we found that cultural variables significantly influence the CO_2 emission intensity. Countries with a low-power distance index and a low uncertainty avoidance index tend to have a higher CO_2 emission intensity, while societies with a low masculinity versus femininity index and a low indulgence versus restraint index tend to have a lower CO_2 emission intensity. Our hypothesis that the individualism versus collectivism index and the long-term versus short-term orientation index have a negative effect on the CO_2 emission intensity are not proved.

However, when the CO_2 emission intensity is corrected for income, the negative effects of the individualism versus collectivism index and the long-term versus short-term orientation index become significant. Income correction also causes the significant sign effects of power distance index, uncertainty avoidance index, individualism versus collectivism index and the long-term versus short-term orientation index changed direction, makes the cubic, quadratic and linear effects of income insignificant. Hence, an increase in the population size of 1% will increase the per capita CO_2 emissions by more than 1%. Furthermore, income correction makes a higher fuel price significantly decrease the CO_2 emission intensity.

Income seems to be the main factor that causes differences in the CO_2 emission intensity between Indonesia and Bangladesh, China and Myanmar. However, the difference in the CO_2 emission intensity between Indonesia and India, Malaysia, Pakistan, the Philippines and Thailand might be caused by differences in the technological progress or by different cultural dimensions, which can influence people's behaviour in consuming energy and could affect the development of technology needed to decrease the CO_2 emission intensity.

The interaction effects between per capita income and culture could change the sign and/or the significance effects of cultural variables. In addition, the interaction effects between per capita income and culture along with clean energy, the energy price and urbanization could change not only the sign and/or the significance effects of cultural variables but also the sign and/or the significance effects of income, population and technology.

In chapter 5 we describe our finding that urbanization affect the energy consumption through income. On the one hand, the technology advantage makes the electrical equipment become more efficient in term of the energy usage. On the other hand, higher income can encourage more people to use electrical equipment or more advance transportation vehicle, that can also increase the energy consumption such as the usage of cellular telephones instead of cable phones or mail by post. air conditioners instead of fans, washing machine instead of washing by hand, motorcycles instead of bicycles, etc. Changing of a life style can also consider as cultural change because cultural change can be though as the process of a new thing or a new method being adopted by a community (Condeluci, 2002). Therefore, we encourage further research on the correlation between the income-emission relationship and cultural variables, to also consider the causality between both variables, that there is a possibility that the income, which related to emission, can affect culture.

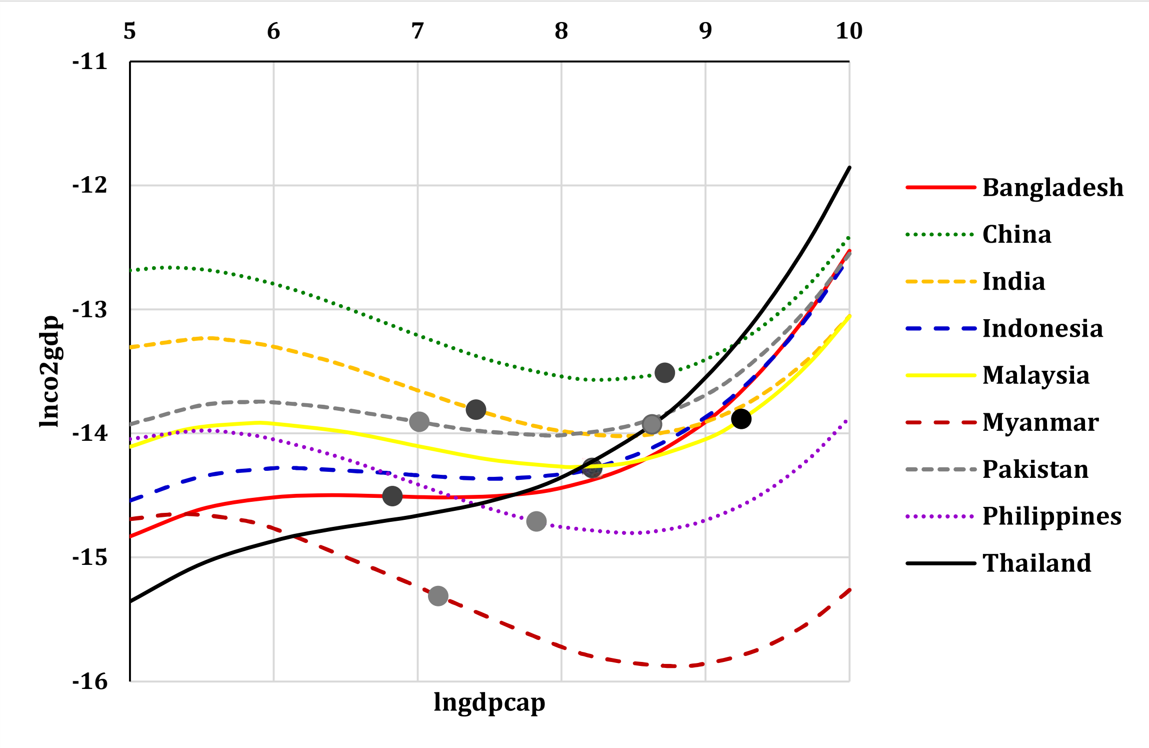
APPENDIX

Table 3.7 – Results of the Mixed-Effect Model with CO_2 per Unit GDP (Constant 2010 US$) as the Dependent Variable (Basic Model)

Independent Variables	Model 3A – Dependent Variable = lnco2gdp									
	All	BGD	CHI	IND	IDN	MYS	MMR	PAK	PHL	THA
Fixed Effects										
lngdpcap3	0.0637 ** (0.0259)	0.0643	0.0645	0.0631	0.0641	0.0629	0.0621	0.0637	0.0630	0.0651
lngdpcap2	−1.3140 ** (0.5520)	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140	−1.3140
lngdpcap	8.7990 ** (3.8834)	8.9190	8.4737	8.7135	8.8782	8.9171	8.7252	8.8296	8.7150	9.0194
lnpop	0.8530 * (0.4385)	1.7858	0.4486	1.3969	1.2343	0.6145	−0.1833	0.9866	0.6862	0.7071
time	−0.0150 ** (0.0068)	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150	−0.0150
cons	−19.4270 (13.5541)	−38.0702	−9.4339	−30.9516	−27.7224	−14.0137	0.2953	−21.7056	−15.0183	−18.2228
Random Effects										
sd(lngdpcap3)	0.0013 *** (0.0005)									
sd(lnpop)	0.5894 *** (0.1607)									
sd(cons)	11.6260 *** (3.0506)									
sd(residual)	0.0921 *** (0.0125)									
Maximum Turning Point	5.7549	6.4011	5.2696	5.4782	6.1289	5.8460	5.3486	5.8507	5.4652	.
Minimum Turning Point	8.0055	7.2234	8.3072	8.3985	7.5272	8.0862	8.7535	7.8912	8.4330	.
Inflection Point	6.8802	6.8123	6.7884	6.9384	6.8280	6.9661	7.0511	6.8709	6.9491	6.7294
Wald Chi^2	24.0000 *** (0.0002)									

Notes: (1) All = all countries, BGD = Bangladesh, CHI = China, IND = India, IDN = Indonesia, KOR = Korea, Rep., MYS = Malaysia, MMR = Myanmar, PAK = Pakistan, PHL = Philippines, SGP = Singapore, THA = Thailand. (2) ln = natural logarithm. The turning and inflection points of per capita real GDP are calculated in natural logarithm. (3) Values in brackets are robust standard errors, sd = standard deviation. (4) The significance level at 1%, 5% and 10% are represented by ***, ** and *, respectively. (5) Random effects for lngdpcap2 and time are not presented due to fixed coefficient values among countries. (6) For the Wald Chi^2, value in the bracket is p-value.

Figure 3.4 – Curve Estimation of CO_2 Emissions per GDP in 2014



Notes: (1) The curve estimation is calculated at the level of population in 2014 for various levels of gdpcap, (2) The dot shows the gdpcap of each country in 2014.

Table 3.8 – Results of the Mixed-Effect Model with per Capita CO_2 Emissions as the Dependent Variable (Extended Model)

Independent Variables	Dependent Variable: $lnco_2gdp$			
	Model 3B1	**Model 3B2**	**Model 3B3**	**Model 3B5**
Fixed Effects				
$lngdpcap^3$	0.0419*** (0.0141)	0.0377 (0.0253)	0.0552*** (0.0131)	0.0311 (0.0296)
$lngdpcap^2$	−0.8538*** (0.3150)	−0.8639 (0.5648)	−1.1990 *** (0.2790)	−0.5636 (0.6845)
Lngdpcap	4.9743** (2.3290)	5.8776 (4.1872)	7.2397*** (1.8891)	2.3509 (8.0301)
Lnpop	−0.8090*** (0.0536)	−0.6369*** (0.1075)	−1.0127*** (0.0491)	−0.2672 (0.2392)
Time	0.0436*** (0.0029)	0.0107** (0.0051)	0.0284*** (0.0021)	−0.0063 (0.0113)
PD	−0.1335*** (0.0040)	−0.0862*** (0.0064)	−0.4249*** (0.0336)	−0.0832 (0.1683)
INV	0.0128* (0.0076)	0.0574*** (0.0131)	0.0866** (0.0374)	−0.0024 (0.1030)
MAS	0.0483** (0.0076)	0.0455*** (0.0113)	0.4843*** (0.0590)	0.1093 (0.1721)
UA	−0.1038*** (0.0118)	−0.0024 (0.0162)	−0.0665 (0.0790)	−0.1807 (0.2131)
LTO	0.0167** (0.0077)	0.0539*** (0.0119)	0.0772* (0.0447)	−0.0086 (0.1303)
IDU	0.0391*** (0.0061)	0.0455*** (0.0083)	0.3018*** (0.0406)	0.0502 (0.0827)
lngdpcapPD			0.0453*** (0.0047)	0.0081 (0.0217)
lngdpcapINV			0.0025 (0.0052)	0.0035 (0.0156)
lngdpcapMAS			−0.0491*** (0.0080)	−0.0155 (0.0209)
lngdpcapUA			0.0200* (0.0112)	0.0205 (0.0311)
lngdpcapLTO			0.0043 (0.0062)	0.0032 (0.0196)
lngdpcapIDU			−0.0303*** (0.0056)	−0.0104 (0.0111)
RenewP		−0.0160*** (0.0025)		−0.0186*** (0.0037)
PGasoline		−0.0363 (0.0611)		−0.1376** (0.0658)
UrbanP		0.0155*** (0.0034)		0.0039 (0.0088)
Constant	−82.4204*** (7.3172)	−35.8890*** (10.1811)	−75.6999*** (7.8965)	8.0552 (25.3387)
Random Effects				
sd (Residual)	0.1698*** (0.0071)	0.0659*** (0.0081)	0.1127*** (0.0048)	0.0556 (0.0063)
Wald Chi^2	5056.3700*** (0.0000)	10867.2700*** (0.0000)	14920.7100*** (0.0000)	10632.4800*** (0.0000)

Notes: (1) PD = the power distance index, INV = the individualism versus collectivism index, MAS = the masculinity versus femininity index, UA = the uncertainty avoidance index, LTO = the long-term versus short-term orientation index and IDU = the indulgence versus restraint index, (2) ln = natural logarithm, (3) The values in brackets are robust standard errors; sd = standard deviation, (4) The significance levels of 1%, 5% and 10% are represented by ***, ** and *, respectively, (5) Random effects are not presented because all the countries have the same coefficient values, (6) For the Wald Chi^2, the value in the brackets is the p-value.

CHAPTER 4 Population Growth and the Trade-off between Green and Brown Expansion of Electricity Supply in Developing Countries: A Spatial Model and Evidence for Indonesia

4.1 Introduction

In many developing countries, poor access to modern energy sources hamper the consumption, production and transportation of goods and services, thereby undermining the economic development. Rapid expansion of the (grid) infrastructure and generating capacity is therefore often a key priority for policy makers in these countries. At the same time, fossil fuel-fired power plants, especially coal-fired power plants, are a leading cause of smog and local air pollution and are among the largest contributors to the emission of greenhouse gases and the associated climate change. Developing countries therefore face a major dual 'energy challenge': the simultaneous expansion and greening of their electricity supply.

In this chapter, we analyse the trade-off between green and brown expansion of the electricity supply in developing countries under the influence of increasing population density by developing a spatial energy model that extends the recent work by Moreno-Cruz & Taylor (2012, 2014, 2017), which we then calibrate to the case of Indonesia. In the archipelagic state of Indonesia, one of the most populous countries in the world, coal-fired power plants are increasingly satisfying the rising demand for electricity. Between 2009 and 2016, the usage of coal by the government-owned electricity company PLN increased from 36% to 50% (PLN, 2010, 2017). However, Indonesia does not necessarily have to follow a coal-oriented development path, like India and China. Indonesia's scattered geography implies relatively large costs to transport coal, and its relatively 'clean infrastructure slate' provides the country with what Collier & Venables (2012) coined a latecomer advantage. This gives the country the potential to exploit a range of low-carbon alternatives relatively quickly; for example, its scattered geography may contribute to favouring decentralized electricity generation in some areas.

It has indeed often been argued that developing countries are in a position to leapfrog the lock-in into fossil fuels by building an energy system that meets their energy requirements from renewable energy resources (Goldemberg, 1998; Perkins, 2003; Collier & Venables, 2012). Despite this strong imperative, recent research has suggested that fossil fuels are likely to remain the dominant source of energy in many regions around the world. Steckel et al. (2015) reported that growth in a broad set of developing countries is increasingly supported by carbon-intensive power generation. As such, it appears that many developing countries are only partially meeting their energy challenge. Moreover, Steckel et al. (2015) showed that the increase in the carbon intensity of energy production is caused mainly by an increase in the consumption of coal. Interestingly, this 'renaissance of coal' is not restricted to China and India but is quite common in emerging economies, especially countries in Asia. As Steckel et al. (2015) and many others (Haftendorn & Holz, 2008; Schiermeier, 2012; Collier & Venables, 2014; Tyfield, 2014; Edenhofer, 2015) have noted, the low price of coal relative to low-carbon alternatives constitutes an important factor for its resurgence and may result in undesirable lock-ins in view of the climate change challenge that the world is facing.

In this chapter, we investigate how this cost advantage of coal vis-à-vis low-carbon alternatives arises from three interrelated features: the geography of the energy supply and energy demand, the power density and technology. As economies grow and develop, the spatial distribution of the population, employment and production changes. Probably the most prominent feature of the spatial transformation in these countries is increased urbanization. In a few decades from now, the global urban population will be larger than the entire global population today, and this urban transition is largely being driven by cities in the developing world, where 90% of the urban growth is projected to take place. This unprecedented change in the geography of economic activity affects economic development and vice versa: an economy's degree of urbanization is not only a consequence of its development but also determines its growth potential (Overman & Venables, 2005; CGD, 2009; Desmet & Henderson, 2014; Duranton & Puga, 2014; Motamed et al., 2014). As noted before, economic development is fuelled by access to modern energy sources, but, if these sources mainly consist of fossil fuels, energy consumption will continue to be a main driver of local air pollution and global greenhouse gas emissions. Most research into the links between global environmental change and economic development has ignored the spatial dimension of both economic development and environmental degradation. In this chapter, we explicitly address the role of space.

The transition to a predominantly urban human population will have a significant impact on the emerging transition to a low-carbon energy system, because there are fundamental physical limits to how much energy we can extract from renewable resources for a given area of land. To measure this, we can calculate an energy source's power density in watts per square metre (W/m^2). 'The power density of an energy resource measures its ability to provide a flow of power considering the area needed for its exploitation' (Moreno-Cruz & Taylor, 2017). The unit cost of transportation of an energy resource is inversely related to its power density, which implies that very power-dense resources, such as coal and oil, will be collected at great distances, while energy resources like timber will not (Moreno-Cruz & Taylor, 2017). In sum, power density is a measure of a resource's 'spatial productivity'. High power density allows for concentration of people and firms in space (Moreno-Cruz & Taylor, 2012; Wilson, 2013; Smil, 2015). Economic historians have commonly held the interplay of energy density and transport costs responsible for the small city sizes in pre-industrial times (e.g. Smil, 2008; Wrigley, 2010). In a similar vein, Nunn and Qian (2011) recently linked the introduction of a new high-density energy source (the lowly potato) to population growth and urbanization in the Old World.

Following the recent work by Moreno-Cruz and Taylor (2012, 2014, 2017), we develop in this chapter a spatial energy model that builds on the concept of power density to analyse the potential trade-off between greening and brown expansion of the electricity supply in developing countries under the influence of increasing population density. We find that, until 2050, the expected population growth in Indonesia leads to about a 35% reduction of the country's share of electricity produced with renewable energy. This result is weakened but not reversed with a substantially higher assumed power density of renewable energy sources. Furthermore, we show that, while a higher elasticity of electricity demand with respect to population density increases the level of electricity generated by renewable sources (the scale effect), it lowers its share of electricity generation (the composition effect). We also find that the lower the population density elasticity of the cost of land, the greater the level and share of green electricity.

The remainder of this chapter is organized as follows. In sections 4.2 and 4.3, we present the spatial theory of the electricity supply chain and the model's equilibrium path of the energy sector. In section 4.4, we briefly review the recent developments in Indonesia's energy and electricity sector and describe the calibration of our model to the Indonesian situation. In section 4.5, we present and discuss our main simulation results. Section 4.6 concludes.

4.2 The Model

4.2.1 Introduction

To understand how geography, power density and technology (of fuel transportation, electricity generation and electricity transmission) influence local electricity diversification, we develop a deterministic partial equilibrium model of the electricity supply chain. We extend the spatial energy model by Moreno-Cruz & Taylor (2014) by incorporating (i) both renewable and non-renewable energy sources, (ii) electricity transmission and (iii) investment in generation capacity. The demand for electricity in a central marketplace can be satisfied by a non-renewable energy fuel, a renewable energy source or a combination of the two. Power density differs between renewable energy and fossil fuels. A non-renewable resource (coal) is more power dense and hence spatially more productive than a renewable resource (solar), which, all things being equal, implies that it is cheaper to transport coal than solar energy. Hence, for a given distance, the transport (or transmission) cost of solar power should exceed that of coal. Because of this, coal will be sourced from a greater distance than solar power and will account for a greater share of the total electricity production. If people, because of urbanization processes, are increasingly concentrated in space, the demand for resources with relatively high 'spatial productivity' will increase: according to the scaling law of Moreno-Cruz & Taylor (2017), the supply of energy from a particular energy source increases with its power density. Hence, the tradeoffs between greening and electricity supply expansion are subject to the distribution of the population and economic development across space.

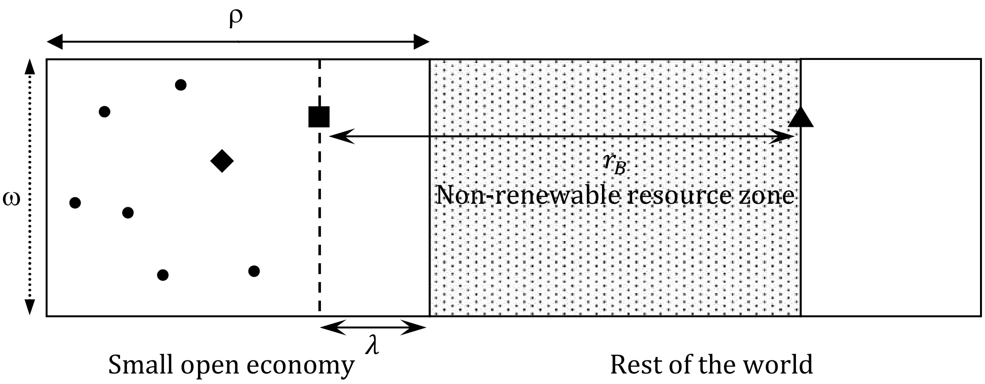
Electricity can be generated by non-renewable energy fuels (e.g. coal, lignite and gas) and renewable energy (e.g. solar, wind and biomass). Two fundamental characteristics drive the supply of these resources in our model. First, wind and solar provide small amounts of (free) energy per square metre of land compared with fossil fuels. In technical terms, renewable energy is characterized by relatively low power density. The diffuse nature of these resources implies that sizeable deployment of renewable energy is dependent on an abundance of cheap and suitable land. Second, as wind and solar energy are free, their costs are primarily driven by the cost of capital associated with capacity investment. Cities' location is fixed (given by history), and they demand electricity. Electricity is generated either by the combustion of fossil fuels in thermal power plants or by renewable generators, for example wind turbines and solar panels. Thermal power plants are located near the cities, and electricity transmission services are needed to transport electricity from producers to consumers.

We analyze four different sectors producing various intermediate goods and services. The non-renewable resource sector extracts fossil fuels from a range of locations across space and then transports these fuels to thermal power plants. Thermal power plant producers buy a non-renewable energy fuel to generate electricity using the available stock of generators. Producers of renewable electricity obtain free solar or wind energy in an amount that is proportional to the installed generation capacity. Both types of producers sell their electricity in the electricity wholesale market to a transmission service operator (TSO). In turn, the TSO delivers electricity through the electricity grid to consumers in the cities. Often, the TSO is the national electricity company, which is, especially in lower- and middle-income countries, usually owned or controlled by the state. All markets, except the consumer electricity market, are characterized by perfect competition. Since the TSO is the only supplier of electricity to consumers, the consumer electricity market is characterized by a monopoly, which we will explain in more detail later.

4.2.2 Geography of Electricity Production

We assume a small open economy zone, which consists of a large city (◆) and several small cities (•). The cities demand electricity, which is produced in a power plant (■) located within the small open economy, outside the human settlements. The big city is located near the power plant, and the small cities are located around the big city (see Figure 1). Energy for electricity production is sourced from renewable and non-renewable resources.

Figure 4.1 – Illustration of a Small Open Economy and Exploitation Zone of Non-Renewable Resources



The non-renewable resources for the thermal power plant are supplied from a mine (▲) located outside the small open economy zone. The distance between the power plant and the mine is r_B (in metres, m). The frontier of the small open economy is located at a distance λ from the thermal power plant. This location also marks the beginning of the non-renewable resource zone, which is located outside the small open economy – implying that, in contrast to renewable resources, non-renewable resources are collected in the world market. Both the domestic and the international zone are characterized by a width ω (m). Last, ρ is the length of the small open economy (see Table 4.1 in the Appendix).

4.2.3 Electricity Market

Electricity Supply

The cities are supplied with the electricity produced by the thermal power plant producer and the producer of green electricity and distributed by the transmission service producer. The net supply of electricity, W_S^e (in watts, W), is the total electricity production minus the electricity loss in the distribution:

$$W_S^e = (1 - L)(W_B^e + W_G^e) \tag{4.1}$$

where L is the fraction of electricity generated from non-renewable resources (B) and renewable resources (G), respectively, that is lost.

Electricity Demand

Electricity demand is the total electricity consumption of the population in the small open economy:

$$W_D^e = i \cdot N^{\beta_W} \tag{4.2}$$

with:

$$i = b - g \cdot p^e \tag{4.3}$$

$$N = A/D \tag{4.4}$$

where i (W/people) is the electricity intensity, b (W/people) is the maximum intensity of electricity consumption, g (W^2/\$·people) is the effect of the consumer electricity price p^e (\$/W) on the electricity intensity with $g > 0$, N (people) is the combined population level of all the cities in the small open economy, A (in square metres, m^2) is the area size of the small open economy, D (people/m^2) is the population density in the small open economy, and β_W is the elasticity of the electricity demand with regard to the population density.[18] Hence, the model can best be interpreted as a single (representative) city model.[19]

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[18] We adjust the formulation in Bettencourt et al. (2007). In their paper, β_W is the elasticity of the electricity demand with regard to the population size.

[19] In principle, we could model energy consumption over a large number of cities as $W_d^e = \sum_{i=1}^{i=N} w_0(n_i)^{\beta_W}$, where n_i is the population size of city i. However, the calibration of the model then requires city-specific data on the elasticity of the electricity demand with regard to the population density, which is as yet unavailable for Indonesia. In addition, on the supply side, where 'D' plays a role in the transmission losses, we have a single city. A multi-city model thus requires us at least to make the length of the electricity grid city specific as well, implying a need to collect city-specific data on transmission losses (which are also as yet unavailable). We therefore leave this for future research.

Market Equilibrium

In market equilibrium, the electricity supply W_S^e (W) equals the electricity demand W_D^e (W):

$$W_S^e = W_D^e \Leftrightarrow (1-L)(W_B^e + W_G^e) = (b - gp^e)N^{\beta_W} \tag{4.5}$$

From this equilibrium condition, it follows that the consumer electricity price in equilibrium is:

$$p^e = \frac{b}{g} - \frac{(1-L)\left(W_G^e + W_B^e\right)}{gN^{\beta_W}} \tag{4.6}$$

Equation (4.6) shows that the consumer electricity price increases with the maximum intensity of electricity consumption (b), distribution losses (L), the small open economy area (A), the population density (D) and the elasticity of the electricity demand with regard to the population density (β_W). The consumer electricity price decreases with the supply of electricity (W_G^e, W_B^e) and the price elasticity parameter of the electricity intensity (g).

Moreno-Cruz & Taylor (2012) focused on explaining how the location and productivity of energy resources determine the distribution of economic activity around the globe. While the distribution of energy resources in the Asia-Pacific region may influence the distribution of economic activity both within and across Indonesia and the surrounding countries, we recognize that there may be other drivers as well. We therefore take the potential demand for electricity as given and then try to explain and predict how various features of geography and technology affect both the overall supply of energy and the energy mix in Indonesia.

4.2.4 Non-Renewable Resource Production

Producers, like mining companies, use a constant-returns-to-scale transportation technology to collect and carry energy fuels from the non-renewable resource zone to the thermal power plant located near the big city. Transporting energy fuels from the mine to the electricity power plant is costly, and the costs increase with the distance and the resource weight. Let us define the physical density of the resource as f_B (kg/m^2) and the exploitation area of the non-renewable resource as A_B (m^2). Then the resource weight x_B (kg) equals $f_B \cdot A_B$. Next, let us define the price of the non-renewable fuel set by the mine producer as p_B^m (\$/W). Producers of brown resources earn revenues $p_B^m \alpha_B A_B$, with α_B (W/m²) being the power density of the non-renewable resource. If we assume that the brown power plant is located in the mouth of the brown resource mine then λ will be zero and producers pay a unit cost u_B (\$/kg·m) per total carry x (kg) over distance r_B (m) of the resource and δ is the total carry cost elasticity with $\delta > 1$, then the producer receives a profit equal to:

$$\pi_B^m = p_B^m \alpha_B \omega r_B - u_B^\delta f_B \omega \int_\lambda^{r_B} r dr = p_B^m \alpha_B \omega r_B - \frac{u_B^\delta f_B \omega {r_B}^2}{2} \qquad (4.7)$$

where m and B refer, respectively, to the mine and the brown/non-renewable resource. Resource producers will extract resources until the marginal revenue from the last unit extracted equals its cost of carry. The marginal supplier in the non-renewable resource zone is indifferent between supplying fossil fuels and not supplying them when the profits have fallen to zero; that is, the marginal revenue from the last unit extracted equals its cost of carry. To find the distance r_B associated with this marginal unit, we set the profits equal to zero:

$$\pi_B^m = 0 \Leftrightarrow r_B^* = 2\frac{p_B^m \alpha_B}{u_B^\delta f_B} \qquad (4.8)$$

$$\Leftrightarrow p_B^m = \frac{u_B^\delta f_B r_B}{2\alpha_B} \qquad (4.9)$$

The right-hand side of equation (4.9) represents the average cost. Furthermore, based on equations (4.7) and (4.8), the higher the resource price and the greater the power density of the resource, the higher the gross revenues from the resource collection and the greater the willingness of the mine producer to explore the resource farther from the power plant and to dig deeper.

To find the net supply of energy for the thermal power plant, note that, across the whole width ω of the resource zone, a total of α_B watts can be collected every metre and delivered to the power plant. Following Moreno-Cruz & Taylor (2014), we do not model energy use in the transportation of resources. To obtain the net resource supply W_B^m for the thermal power plant, we sum the net 'physical resource rents' over the whole area of exploitation:

$$W_B^m = \int_\lambda^{r_B} \omega \alpha_B dr = \alpha_B \omega r_B = \alpha_B A_B \qquad (4.10)$$

From (4.10), we find that the higher the power density, the larger the supply of non-renewable resources for the thermal power plant. This is because the power density increases the supply of energy not only via the intensive margin, that is, it boosts the supply of energy from infra marginal lands, but also via the extensive margin, that is, it increases the supply of energy by extending the resource frontier outwards. Equation (4.10) also reveals that, if the non-renewable resource zone is located far away from the power plant, then the net supply for the power plant decreases. In the absence of new resource discoveries, the consumption of non-renewable resources will thus first peak and then decline (Moreno-Cruz & Taylor, 2014).

This boom–bust pattern has already become apparent for Indonesia, where the declining production of oil fuel has forced Indonesia to become more reliant on domestic coal production and imports of fossil fuels, possibly turning Indonesia into a net energy importer before 2019 (Indonesian DGNEEC, 2012). Equation (4.10) explains why, in some remote areas, local resources with much lower power density have not been exploited and why those areas are still more dependent on non-renewable resources. However, the long delivery distance for the resource causes high costs. For example, the cost of providing oil fuel (including the transport cost) was \$1.52 per liter in the remote province of Papua (Indonesia) in 2013.[20] This is more than one and a half times the price of non-subsidized oil fuel at \$0.8–0.9 per liter.[21] Including the maintenance cost, the electricity production cost per kWh is 38¢, considerably higher than the average basic electricity tariff of only 7¢ per kWh (Dhany, 2013). The high cost lowers the electricity supply and results in relatively frequent power outages in remote areas.

4.2.5 Wholesale Electricity Production

Brown Electricity

The producer of brown electricity, that is, the thermal power plant, buys non-renewable resources at price p_B^m, converts them into electricity at the efficiency rate

[20] The IDR value was converted into USD based on the average exchange rate in 2013 (Bank Indonesia, 2015).
[21] In 2017, President Joko Widodo commanded a uniform oil fuel price in all areas in Indonesia (Irfany, 2017).

η_B with $0 < \eta_B < 1$ and sells electricity on the wholesale electricity market to the TSO at price p_B^e [\$/W]. Abstracting from the operation and maintenance costs, the thermal power plant's profits equal:

$$\Pi_B^e = p_B^e W_B^e - p_B^m W_B^m - I_B k_B \tag{4.11}$$

where e refers to the electricity producer and I_B (\$/W) is the investment cost of the thermal power plant per unit of installed capacity, k_B (W). Brown electricity production W_B^e (W) can never exceed full capacity, so:

$$W_B^e = \eta_B W_B^m = z_B k_B \leq k_B \tag{4.12}$$

where z_B is the rate of production at the brown power plant, with $0 \leq z_B \leq 1$. If $z_B = 1$, then the power plant produces at full capacity.

Using equations (4.9), (4.10) and (4.12), we can reformulate equation (4.11):

$$\Pi_B^e = \left(\left(p_B^e - \frac{I_B}{z_B}\right)\eta_B \alpha_B - \frac{u_B^\delta f_B (r_B + \lambda)}{2}\right) A_B \tag{4.13}$$

Equation (4.13) demonstrates that the higher the price of brown electricity and the efficiency rate in the thermal power plant, the greater the power density of the resource, the wider the exploitation area of the resource and the larger the profit of the brown electricity producer. Equation (4.13) also indicates that the higher the investment cost and the unit cost of carry, the heavier the resource weight collected per square metre of the exploitation area, the farther the distance between the power plant and the resource mine, the lower the production rate in the power plant, the greater the cost and the lower the profit of the brown electricity producer.

With the market for brown generation capacity being perfectly competitive, investors will increase the capacity until the profits are equal to zero. Setting the right-hand side of equation (4.11) equal to zero, and rearranging, we obtain:

$$k_B = \left(\frac{p_B^e \eta_B - p_B^m}{I_B}\right) W_B^m = 2\omega \left(\frac{p_B^e \eta_B - p_B^m}{I_B}\right)\left(\frac{\alpha_B^2}{u_B^\delta f_B} p_B^m\right) \tag{4.14}$$

We assume that the brown electricity producer is a non-profit firm that works under zero economic profit. Using equations (4.9) and (4.12), the zero-profit condition can be written as:

$$\Pi_B^e = 0 \Leftrightarrow p_B^e = \frac{I_B}{z_B} + \frac{u_B^\delta f_B r_B}{2\eta_B \alpha_B} \tag{4.15}$$

According to equation (4.15), the higher the investment costs and the unit cost of total carry, the heavier the resource and the farther the distance between the power plant and the resource mine, then the higher the price of brown electricity. In contrast, the higher the production and efficiency rates in the thermal power plant and the larger the power density of the resource, the lower the brown electricity price.

Green Electricity

The producer of green electricity collects energy from renewable energy sources, like sunlight, wind and geothermal heat, converts this into electricity at the efficiency rate η_G with $0 < \eta_G < 1$ and sells the green electricity on the wholesale electricity market to the TSO at price p_G^e (\$/W). We assume that the green electricity producer only needs to cover investment costs, because, for many renewable energy technologies, the renewable resources (like wind and sun) can be collected for free at the power plant. Hence, the profit function of the green electricity producer is:

$$\Pi_G^e = p_G^e W_G^e - I_G k_G \tag{4.16}$$

where G refers to the green or renewable resource and I_G (\$/W) is the investment and maintenance cost of the green power plant per unit of installed capacity, k_G (W). We assume that the costs for generating green power decrease with the power density α_G and the efficiency rate η_G with which the flow of renewable resources can be exploited (IRENA, 2015) but increase with population density D because this reduces the potential exploitation area of the renewable resource (A_G). An increasing demand for residential land area implies increasing scarcity of suitable land to harvest green energy from hydro dams, windmills, biomass crops and solar farms and thus higher production costs.

We model these various effects as follows:

$$I_G = I_G^k + \frac{\psi_G}{\eta_G \alpha_G} I_G^L = I_G^k + \frac{A_G}{\eta_G \alpha_G A} I_G^L \tag{4.17}$$

with I_G^k (\$/W) being the cost of the green power equipment (like solar panels), I_G^L (\$/m²) being the cost of the land area needed for green power production, ψ_G ($0 < \psi_G < 1$) being the share of the small open economy area (A) that is used for the green energy production (so $A_G = \psi_G$A) and the other parameters being as before.[22] The supply of green electricity production, W_G^e (W), depends on the renewable resource supply (W_G^r) and the efficiency rate of green power production (η_G). Furthermore, we assume that green power plants always run at full capacity, implying that the rate of production at the green power plant $z_G = 1$.[23] This implies that:

$$W_G^e = \eta_G W_G^r = z_G k_G = k_G \tag{4.18}$$

The net renewable resource supply (W_G^r) to the green power plant(s) is defined by the amount of renewable watts that can be collected from every square metre – the power density α_G – across the exploitation area A_G of the renewable resource at a cost of I_G^L (\$/m²), with the exploitation area being defined by its width ω and length ρ (see Figure 1). We do not model energy use or other costs in the transportation of resources.[24] Hence, the net 'physical resource rents' over the whole area of exploitation are:

$$W_G^r = \alpha_G \omega \rho \psi_G = \alpha_G \psi_G A = \alpha_G A_G \tag{4.19}$$

Using equations (4.18) and (4.19), we can reformulate equation (4.16) as:

$$\Pi_G^e = (p_G^e - I_G)\eta_G \alpha_G \psi_G A \tag{4.20}$$

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[22] We could assume that the costs for generating green power decrease with the cumulative installed production capacity K_G because of a technology learning effect (IRENA, 2016), such that $I_G^{\mathrm{k}} = aK_g{}^{-b}$. However, this would complicate the model without yielding additional insights for the purpose of our analysis. Therefore, we take I_G^{k} as a fixed cost, implicitly assuming that learning effects materialize in the world market from which green power equipment is imported.

[23] This assumption implies that solar panels and windmills are never switched off, which is a reasonable assumption (especially for solar panels, the most important source of renewable energy in Indonesia).

[24] These costs are zero by definition in the case of electricity production from solar, wind and hydro but may be positive in the case of burning biomass.

Equation (4.20) shows that the green electricity profits increase with the green electricity price and decrease with the cost of investment, subject to the efficiency rate of green power production (η_G), the power density of the renewable resource (α_G), the size of the small open economy area (A), the share of the small open economy area that is used for green energy production (ψ_G) and the cost of the land area needed for green power production (I_G^L). With the market for renewable generation capacity being perfectly competitive, investors will find it worthwhile to increase the capacity until the green electricity price equals the effective per unit cost of capital. Setting the right-hand side of equation (4.20) equal to zero, using equations (4.17) and (4.19) and rearranging equation (4.18), we obtain:

$$k_G = \left(\frac{p_G^e \eta_G}{I_G}\right) W_G^r = \left(\frac{p_G^e \eta_G}{I_G}\right) \alpha_G \psi_G A = \left(\frac{p_G^e \eta_G}{I_G^k + \frac{\psi_G}{\eta_G \alpha_G} I_G^L}\right) \alpha_G \psi_G A = \frac{p_G^e (\eta_G \alpha_G)^2 A \psi_G}{I_G^k \, \eta_G \alpha_G + I_G^L \psi_G} \quad (4.21)$$

According to equation (4.21), the installed capacity of green power production increases with the green electricity price (p_G^e), the efficiency rate of green power production (η_G), the power density of the renewable resource (α_G) and the size of the open economy area, while it decreases with the cost of the green power equipment, such as solar panels (I_G^0 [\$/W]), and the price of land for green energy production (I_G^L).

We assume that the green electricity producer is a non-profit firm that operates under zero economic profit. Using equation (4.17), the zero-profit condition for equation (4.20) can be written as:

$$\Pi_G^e = 0 \Leftrightarrow p_G^e = I_G^k + \frac{\psi_G}{\eta_G \alpha_G} I_G^L \quad (4.22)$$

According to equation (4.22), the higher the land and equipment investment cost and the larger the share of the small open economy area that is used for green energy production, the higher the price of green electricity. In contrast, the larger the power density of the renewable resource and the higher the efficiency rates in the power production plant, the lower the green electricity price.

4.2.6 Transmission of Electrical Power

Transmission Technology and the Electricity Grid

We assume that the thermal power station is located outside the large city (◆), creating a natural demand for the transportation of electrical power from the producer to the consumers. Since their inception in the nineteenth century, electricity grids have enabled the transportation of electrical power across long distances. The bulk of electricity is transferred, or transmitted, along high-voltage power lines from power stations to electrical substations. Central to the final stage of the delivery of electricity to consumers is a finer-grained collection of power lines, a part of the infrastructure often referred to as the distribution grid. Together the transmission and the distribution grid are referred to as the electricity grid. The transmission of electrical power depends on the geographic distribution of power producers and electricity consumers. For green electricity, we assume that it can be generated by a utility-scale solar power plant that is also located outside the city, but the green electricity generator may also be installed at the consumer's residency, for example a set of solar panels that is placed on the roof.

The larger the electricity grid, that is, s (metre circuit, mc), the more expensive the distribution of electricity will be. Moreover, if people cluster in the large city (◆), fewer lines are required. On the other hand, if people are scattered in small cities (•) or the countryside, more lines are needed. Therefore:

$$L = \tau s = \tau \gamma D^{-\beta_s} \tag{4.23}$$

with:

$$s = \gamma D^{-\beta_s} \tag{4.24}$$

where L is losses, τ (%/mc) is the effect of the distribution distance on the electricity loss, γ is the effect of the population density on the length of the distribution line[25] and β_s is the elasticity of the population density on the electricity loss along the length of the distribution line. We assume that $\beta_s > 0$.[26] Since the thermal power plant cannot

[25] If $\beta_s = 1$, then the unit measurement for γ is mc·people/m^2.

[26] Notice that, in our model, the elasticity measures the effect of the population density on the electricity loss or the length of the distribution line, while Bettencourt et al. (2007) present the effect of the population size on the length of the distribution line.

be located in the cities, brown electricity always needs the transmission service, so $\gamma > 0$.

Transmission Service Operator

The transmission service operator buys power at the price p_B^e for electricity generated from the non-renewable resource and at the price p_G^e for electricity generated from the renewable resource and sells electricity to consumers in the small open economy at price p^e ($/W),[27] taking into account the fact that the electricity supplied suffers from transmission losses:

$$\Pi_T^e = \left((1-L)p^e - p_B^e\right)W_B^e + \left((1-L)p^e - p_G^e\right)W_G^e - cs \qquad (4.25)$$

where c is the transmission service cost per mc of the length of the line in the distribution.

Rewriting equation (4.25) using equations (4.10), (4.12), (4.15), (4.18), (4.19), (4.22), (4.23) and (4.24) gives us:

$$\Pi_T^e = \left(\left(1 - \tau\gamma D^{-\beta_s}\right)p^e - \frac{I_B}{z_B} - \frac{u_B^\delta f_B r_B}{2\alpha_B \eta_B}\right)\eta_B \alpha_B A_B$$
$$+\left(\left(1 - \tau\gamma D^{-\beta_s}\right)p^e - I_G^k - \frac{\psi_G}{\eta_G \alpha_G}\, I_G^L\right)\eta_G \alpha_G A_G - cs \qquad (4.26)$$

Equation (4.26) reveals that the profits of the transmission service producer increase with the price of electricity, the power plant efficiency rate, the power density of the energy resources, the resource exploitation areas and the production rate at the generator. The profits decrease with the electricity loss per unit of length of the distribution line, the effect of the electricity generation technology on the length of the distribution line and the cost of investment. Furthermore, a higher population density and lower elasticity of the line distance with respect to the population density reduce the transmission cost and raise the profits.

A higher cost to deliver the resource from the mine to the thermal power plant, a greater weight of the brown resource and a greater distance between the thermal power plant and the mine reduce the profits of the TSO.

[27] The electricity price in reality is the price of energy ($/kWh), but the electricity price in our model is the price of electrical power ($/W). Power is energy per unit of time. We convert the price in $/kWh into $/W by assuming that the time is one year.

4.3 Model Equilibrium

To close the model, we assume that it is the objective of the transmission service operator (TSO) to maximize its profits by choosing the optimal mix of brown and green electricity from the electricity producers, subject to the equilibrium condition (4.5), in which the total electricity supply equals the total electricity demand of consumers. By substituting equation (4.6) into equation (4.25), the profit function of the TSO reads as:

$$\Pi_T^e = \left(\frac{b}{g}(1-L) - p_B^e\right) W_B^e + \left(\frac{b}{g}(1-L) - p_G^e\right) W_G^e - \frac{2(1-L)^2}{gN^{\beta_W}} W_B^e W_G^e \\ - \frac{(1-L)^2}{gN^{\beta_W}} {W_B^e}^2 - \frac{(1-L)^2}{gN^{\beta_W}} {W_G^e}^2 - cs \tag{4.27}$$

The first-order conditions for the maximization of Π_T^e are:

$$\frac{\partial \Pi_T^e}{\partial W_B^e} = 0 \Leftrightarrow \frac{b}{g}(1-L) - p_B^e - \frac{2(1-L_B L)^2}{gN^{\beta_W}} W_G^e - \frac{2(1-L)^2}{gN^{\beta_W}} W_B^e = 0 \tag{4.28}$$

$$\frac{\partial \Pi_T^e}{\partial W_G^e} = 0 \Leftrightarrow \frac{b}{g}(1-L) - p_G^e - \frac{2(1-L_B L)^2}{gN^{\beta_W}} W_B^e - \frac{2(1-L)^2}{gN^{\beta_W}} W_G^e = 0 \tag{4.29}$$

Rearranging equations (4.28) and (4.29) yields the optimal quantities of brown (W_B^e) and green (W_G^e) electricity, respectively:

$$W_B^e = \frac{gN^{\beta_W}}{2(1-L)^2}\left[\frac{b}{g}(1-L) - p_B^e\right] - W_G^e \tag{4.30}$$

$$W_G^e = \frac{gN^{\beta_W}}{2(1-L)^2}\left[\frac{b}{g}(1-L) - p_G^e\right] - W_B^e \tag{4.31}$$

From equations (4.30) and (4.31), it can be seen that the optimal quantity of both brown and green electricity increases with the small open economy area (A), the population density (D), the elasticity of the electricity demand with regard to the population density (β_W) and the maximum intensity of the electricity consumption (b). Furthermore, the optimal quantity of green (brown) electricity increases with distribution losses and the production price of brown (green) electricity.

To specify W_B^{e*} and W_G^{e*} further, we make use of equations (4.10) and (4.12) to define r_B as a function of W_B^e:

$$W_B^e = \eta_B W_B^m = \eta_B \alpha_B \omega r_B \Leftrightarrow r_B = \frac{1}{\eta_B \alpha_B \omega} W_B^e \tag{4.32}$$

and we make use of equations (4.18) and (4.19) to define η_G as a function of W_G^e:

$$W_G^e = \eta_G W_G^r = \eta_G \alpha_G \omega \rho \psi_G = \eta_G \alpha_G \psi_G A \Leftrightarrow \eta_G = \frac{1}{\alpha_G \psi_G A} W_G^e \tag{4.33}$$

Next, we substitute (4.31) and (4.32) into (4.30) and (4.30) and (4.33) into (4.31). In doing so, we make use of $p_B^e = \frac{I_B}{z_B} + \frac{u_B f_B r_B}{\eta_B \alpha_B}$ from equation (4.15) and $p_G^e = I_G^{\mathrm{k}} + \frac{\psi_G}{\eta_G \alpha_G} I_G^L$ from equation (4.22). After rearranging, we obtain:

$$W_B^{e*} = 2\omega \frac{(\alpha_B \eta_B)^2}{u_B^\delta f_B} \left(p_G^e - \frac{I_B}{z_B}\right) \tag{4.34}$$

$$W_G^{e*} = A \frac{(\eta_G \alpha_G)^2}{I_G^L} \left[\left(\frac{I_B}{z_B} + \frac{u_B^\delta f_B r_B}{\eta_B \alpha_B}\right) - I_G^{\mathrm{k}}\right] \tag{4.35}$$

Thus, the optimal quantity of green electricity increases with the production price of brown electricity. On the other hand, equation (4.34) shows that the optimal quantity of brown electricity increases with the production price of green electricity.

Next, let us make the following assumptions:

A1. The green electricity price net of transmission losses is strictly larger than the first unit of brown electricity delivered, $p_G^e > \frac{I_B}{z_B}$.

A2. The electricity demand is sufficiently large, that is,

$$2\omega \frac{(\alpha_B \eta_B)^2}{u_B^\delta f_B} \left(p_G^e - \frac{I_B}{z_B}\right) < \frac{iN^{\beta w}}{1-L}$$

We can then summarize our findings in the following propositions.

Proposition 1. *Assume that A1 and A2 hold. The equilibrium pair* (W_B^{e*}, W_G^{e*}) *represented by equations* (4.34)–(4.35) *is then strictly interior, that is,* $(W_B^{e*}, W_G^{e*}) > (0,0)$.

In equilibrium, the level of brown electricity produced increases (and the level of green electricity produced decreases) with the width of the non-renewable exploitation area, the resource and production efficiency of the thermal power plant, the power density of the non-renewable resource, the share of the total land area devoted to green power production, the unit price (or cost) of green electricity, the green transmission losses and the population density.

On the other hand, the level of green electricity produced increases (and the level of brown electricity produced decreases) with the size of the open economy area, the efficiency rate of green power production, the power density of the renewable resource, the unit price (or cost) of brown electricity, the brown transmission losses and the transport costs of the non-renewable resource to the thermal power plant.

From equations (4.17), (4.22) and (4.34), it follows that, in equilibrium, a large share of the total land area devoted to green power production (ψ_G) increases the level of brown electricity produced. The reason for this result is that the more land is used for green power production, the scarcer suitable land to harvest green energy will be, thus increasing the costs of land for green power production and therefore the unit price (or cost) of green electricity. At the same time, in section 2.5, we argued that the potential renewable exploitation area will also become scarcer under the influence of an increasing population density (D) because of the implied increasing demand for residential land. Let us assume that the costs of land for green power production (I_G^L) depend on the population density (D) according to:

$$I_G^L = \theta D^{\beta_L} \tag{4.36}$$

where $0 < \beta_L < 1$ is the elasticity of land prices with respect to the population density. Combining equation (4.36) with the definitions of population density and the share ψ_G of the small open economy area (A) that is used for green energy production as given in, respectively, equations (4.4) and (4.17) allows us to define how the green electricity price (see equation (4.22)) depends on the population size, the size of the renewable exploitation area A_G and its share ψ_G in the small open economy area (A):

$$p_G^e = I_G^k + \frac{\psi_G}{\eta_G \alpha_G} \theta D^{\beta_L} = I_G^k + \frac{\theta {\psi_G}^{1+\beta_L}}{\eta_G \alpha_G} \left(\frac{N}{A_G}\right)^{\beta_L} \tag{4.37}$$

This leads to the following proposition:

Proposition 2. *The green electricity price (and thus the level of brown electricity produced) increases with the population size, the share of the total land area devoted to green energy production and the elasticity of land prices with respect to the population density.*

On the other hand, the green electricity price (and thus the level of brown electricity produced) decreases with the efficiency rate of green power production, the power density of the renewable resource and the size of the renewable exploitation area.

Hence, we find that the role of an increase in the renewable exploitation area in greening the electricity supply is ambiguous, since it depends on the elasticity of land prices with respect to the population density (β_L) and population size. Increasing the renewable exploitation area stimulates green electricity production only if the elasticity of land prices with respect to the population density and the population size is small. To gain further insight into the role of a growing population in the greening of the electricity supply, we substitute equation (4.34) into the equilibrium condition (4.5) to obtain:

$$W_G^{e*} = \frac{(b-gp^e)N^{\beta W}}{(1-L)} - W_B^{e*} = \frac{(b-gp^e)N^{\beta W}}{(1-L)} - 2\omega \frac{(\alpha_B \eta_B)^2}{u_B^{\delta} f_B}\left(p_G^e - \frac{I_B}{z_B}\right) \tag{4.38}$$

From equation (4.38), it follows that a higher population density (D) on the one hand increases the equilibrium level of green electricity (W_G^{e*}) through a higher demand $(b - gp^e)N^{\beta_W}$ (g > 0), subject to the elasticity of the electricity demand with regard to the population density (β_W). On the other hand, a higher population density (D) decreases the equilibrium level of green electricity (W_G^{e*}) by increasing the equilibrium level of brown electricity (see proposition 1). The latter effect reflects the economies of scale and scope in the production and distribution of brown electricity with a relatively high power density, as discussed before. We need to simulate our model to learn the total effect of the population density on greening the electricity supply in Indonesia.

Finally, inserting equations (4.34) and (4.35) into equation (4.27) gives us the maximum profit obtained by the TSO. By substituting L_B and L_G from equation (4.23) and (4.24), we can write the maximum profit of the transmission service producer as a function of the population density:

$$\Pi_T^{e\,*} = \left(\frac{b}{g}\left(1 - \tau\gamma D^{-\beta_s}\right) - p_B^e\right) W_B^{e\,*} + \left(\frac{b}{g}\left(1 - \tau\gamma D^{-\beta_s}\right) - p_G^e\right) W_G^{e\,*}$$
$$- \frac{2\left(1-\tau\gamma\gamma_B D^{-\beta_s}\right)^2}{gN^{\beta_W}} W_B^{e\,*} W_G^{e\,*} - \frac{\left(1-\tau\gamma D^{-\beta_s}\right)^2}{gN^{\beta_W}} W_B^{e\,*2} - \frac{\left(1-\tau\gamma D^{-\beta_s}\right)^2}{gN^{\beta_W}} W_G^{e\,*2} \quad (4.39)$$

Equation (4.39) can be used to determine the population density threshold for a certain level of maximum profits of the TSO.

4.4 Model Calibration and Simulations

In this section, we first describe the major developments in the electricity system in Indonesia, including a brief portrayal of its institutional context. Next, we briefly describe the calibration of our model to the Indonesian situation.

4.4.1 The Electricity System in Indonesia

As noted in the introduction, Indonesia could in principle benefit from a 'latecomer advantage' to develop a low-carbon electricity system, but it is currently increasingly using coal-fired power plants to meet its rising demand for electricity. It is also one of the most populous countries in the world. In combination with rising per capita income, continued urbanization and its archipelagic geography, this imposes formidable challenges for its national electricity company (PLN) in terms of expanding and greening its electricity. Most Indonesian residents obtain their electricity from PLN, the state electricity company in Indonesia, which also buys electricity from independent power producers (IPPs) and private power utilities (PPUs).[28] Besides producing electricity, PLN is responsible for most of the electricity distribution. Hence, PLN corresponds well with the transmission service operator (TSO) in our model.

[28] Independent power producers (IPPs) are private companies that own power plants to produce electricity for sale to the public under a power purchase agreement (PPA), whereas private power utilities (PPUs) are private companies that generate, transmit and distribute electricity to their own customers in a certain area (Austrade, 2012). The Indonesian Government is also developing an energy self-sufficient villages (ESSV) programme. An ESSV is a village that is able to generate at least 60% of its electricity and fuel need from local renewable energy resources (Indonesian MEMR, 2014).

PLN is facing challenges in realizing much-needed investments in the maintenance and expansion of its generating capacity and network infrastructure. An important reason for this is that the Government of Indonesia regulates the electricity prices and for years has forced PLN to sell electricity under its long-term cost price. The government subsidies for PLN were only sufficient to cover its operational costs (Heriyono & Yopi, 2009), and they have been reduced in recent years. As a result, the consumer electricity price has increased substantially over the last few years.[29] According to the draft of the *National Electricity General Plan 2015–2034* (Indonesian MEMR, 2015), Indonesia needs to meet an additional power demand of 784 TWh generating capacity until 2034 (compared with 2014). During the period 2015–2019, the Government is planning to build 35 GW extra power-generating capacity. PLN is responsible for realizing about 29% of this capacity increase, while the rest should be developed by the private sector (Indonesian MEMR, 2017).

The national energy policy in Indonesia aims to increase the share of renewable energy from 5% in 2013 to 23% in 2025 and 31% in 2050 (Indonesian MEMR, 2015). In 2015, 90% of PLN's electricity production and purchasing came from non-renewable resources (Indonesian MEMR, 2017). Although PLN has been successful in reducing its dependency on oil fuels from 29% in 2009 to 11% in 2015, the usage of coal and gas as fuels has increased from 36% in 2009 to 52% in 2015 and from 24% in 2009 to 29% in 2015, respectively (PLN, 2010, 2017). In the longer run, this transition from oil fuel to gas and coal is under pressure, because the natural gas production in Indonesia is tied up in long-term contracts (Hutagalung & Hartono, 2012; Kompas, 2014) and the coal reserves are depleting, while the need for gas and coal is increasing with the construction of new thermal power plants.[30] In addition, coal producers are inclined to sell their products abroad, because this is more profitable (Sutianto, 2014).

[29] The increase in the electricity price sold by PLN is regulated by the Ministry of Energy and Mineral Resources. Since 2015, the basic electricity tariff for household consumers with minimum power of 1300 VA has been adjusted every month. With the adjustment price, the highest price increase for households with power 1300 VA was in December 2015, with a price increase of 38.5% compared with the price in July–August 2014. The price adjustment for households with power of 900 VA has been applied since 2017. The price increase in July–September 2017 was 123.5% compared with the price in July–August 2014. For a household with power of 450 VA, the price has remained stable.

[30] In 2016, the coal reserves and production in Indonesia were 28,457.29 million tons and 456,197,775 tons, respectively (Indonesian MEMR, 2017). Assuming that no new reserves are found at the current production rate, coal in Indonesia will be exhausted in about 62 years.

Together, this raises the need for the Government to keep developing new electricity-generating capacity based on renewable resources. Most of PLN's current production and purchasing of green electricity is generated from hydro-power (5.9%) and geothermal energy (4.3%), plus a small amount from biomass (0.2%), waste (0.008%), solar power (0.002%) and wind power (0.002%). According to PLN's business plan (Indonesian MEMR, 2017), about 41% of the additional power plant capacity in 2017–2026 will come from coal steam power. Nonetheless, about 27.7% is supposed to come from renewable resources, such as hydropower (18%), geothermal (8.1%) and wind, solar, waste and biomass (1.6%).

The electrification ratio in Indonesia was 91.16% in 2016 (Indonesian MEMR, 2017), but the spatial distribution of electricity access is uneven. The electrification ratio in Java was 91.73%, while outside Java it was on average only 83.28%, with the lowest electrification rate being 45.93% in the West Papua province (Indonesian DGE, 2016). Most of the areas lacking access to electricity are remote areas. Their geographic conditions make it difficult to build power plants and develop and maintain an electricity distribution network.

4.4.2 Model Calibration

We calibrate the model in this chapter using data from Indonesian and international sources, such that the model reflects the electricity system in Indonesia in 2015. After that, we use the model to simulate the effect of some changes in the parameters in the model on the profit of the transmission producer and the share of green electricity. More precisely, we use the model to find the production of brown electricity (W_B^e) and the production of green electricity (W_G^e) that maximize the profit of the TSO (Π_T^e), given the changes in the population density (D) over time.

Land area, population size and population density values are taken from the World Development Indicators database (World Bank, 2017). The population density in Indonesia from 2016 to 2050 is assumed to grow at 23%, a value that we take from the United Nations (2017) for the medium-growth scenario. We measure the length of the economy from the distance between Sabang (the northernmost and westernmost city) and Merauke (the easternmost regency). The effect of the population density on the length of the line needed to distribute brown electricity is estimated based on equation (24) using the line length, population density and elasticity of the electricity loss with regard to the population density. Because of the lack of data, we assume that the length of the line needed to distribute brown electricity is proportionate to the brown electricity production. We set the distance between the thermal power plant and the border between the small open economy and the exploitation area of the brown resources at zero (as if the power plant is on the border between the small open economy and the exploitation area of the brown resources). The reason is that we cannot easily obtain a true value, given that there are many power plants in many locations. By setting the value at zero, the effect of parameter changes in the simulation on the distance between the power plant and the mine (r_B) can be shown clearly. The distance between the power plant and the mining of brown resources is estimated based on the brown electricity production (Indonesian MEMR, 2017) as well as the estimated brown power density and the brown efficiency rate in 2016. The share of the green exploitation area is estimated based on the green electricity production in 2016 (Indonesian MEMR, 2017), the estimated green power density and the green efficiency rate in 2016, the width of the Indonesian area ($\omega = \frac{A}{\rho}$) and the distance between the small open economy and the exploitation area of the brown resources.

Because coal steam power is dominant in Indonesia, the power density of brown resources is estimated based on the coal power density in coal power plants (Donald, 2016), while the power density of green resources is based on the average solar radiation in Indonesia (Indonesian DGNREEC, 2013). The value for the physical density of the brown resource is based on the normal weight of coal (145 tons) from a 1 acre area with thickness of 30 inches (The Kentucky Foundation, 2007). The efficiency rate of the thermal power plant is based on the average thermal efficiency rate in Indonesia in 2016, while the efficiency rate for green electricity production is estimated on the basis of the efficiency rate of solar panels (c-Si type) in 2003 and 2012 (IEA, 2014; IRENA, 2015). The unit delivery cost of the brown energy resource from the mine to the thermal power plant is based on the maximum coal transport costs by train in Indonesia in 2016 (IDOMINING, 2016). The actual production rate in the thermal power plant is estimated based on the installed capacity and electricity production in Indonesia during the period 2001–2016. The unit investment costs of thermal power plants are based on an estimation of the investment costs of coal steam power plants per year of lifetime. The maximum unit investment costs of green power plants are based on the investment in solar power plants per year of lifetime (IRENA 2016).

The elasticity of the electricity loss or the line length with regard to the population density is estimated based on data about electricity losses in transmission and distribution and data for the population density in Indonesia during the period 1990–2016. The elasticity of the electricity demand with regard to the population density is estimated based on the average total electricity sales and the population density of Indonesia during the period 1989/1990–2015. Since we do not have information about the land investment costs for green power plants, we set the elasticity of the costs of green land area with regard to the population density at 1. The electricity price is based on the average electricity selling price in Indonesia in 2016. The intensity of electricity consumption is estimated based on PLN's electricity sales in 2016 (Indonesian MEMR, 2017). The effect of the electricity price on the electricity consumption intensity is estimated based on the estimated electricity consumption intensity and the average selling price during the period 2001–2015. The effect of the length of the line on the transmission and distribution loss is estimated based on the electricity loss in the transmission and distribution and the total line length of low, medium, high and extra high voltage in Indonesia in 2016.

Most of the data used to estimate the parameter values in the model come from the Indonesian Ministry of Energy and Mineral Resources, PLN and the World Bank, but some are taken from other sources (see Table 4.1 in the Appendix).

4.5 Simulation Results

In this section, we present our most important simulation results. The simulations are presented in Figures 4.2–4.6. In Figure 4.2 we show the electricity demand under the scenario of low, medium and high growth. The first key result, as shown in Figures 4.3–4.6, is that increasing population density over time leads to an expected decreasing share of green electricity production.

Figure 4.2 – The Electricity Demand under the Influence of Changing Population Density (D)

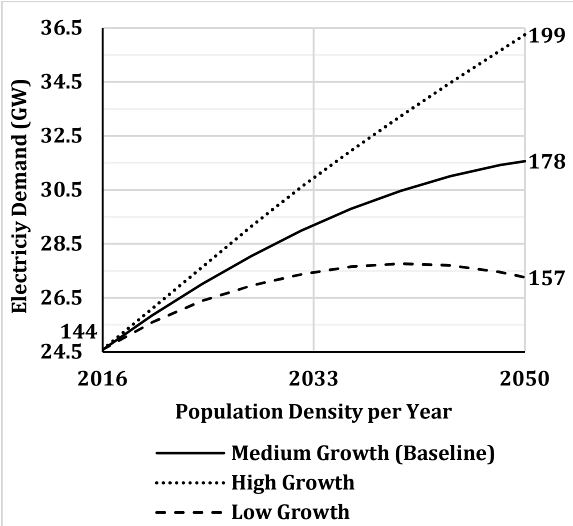


Figure 4.3 – The Share of Green Electricity under the Influence of Changing Population Density (D) (Top-Left) and the Elasticity of the Electricity Demand with Respect to the Population Density (β_W) (Top-Right & Bottom)

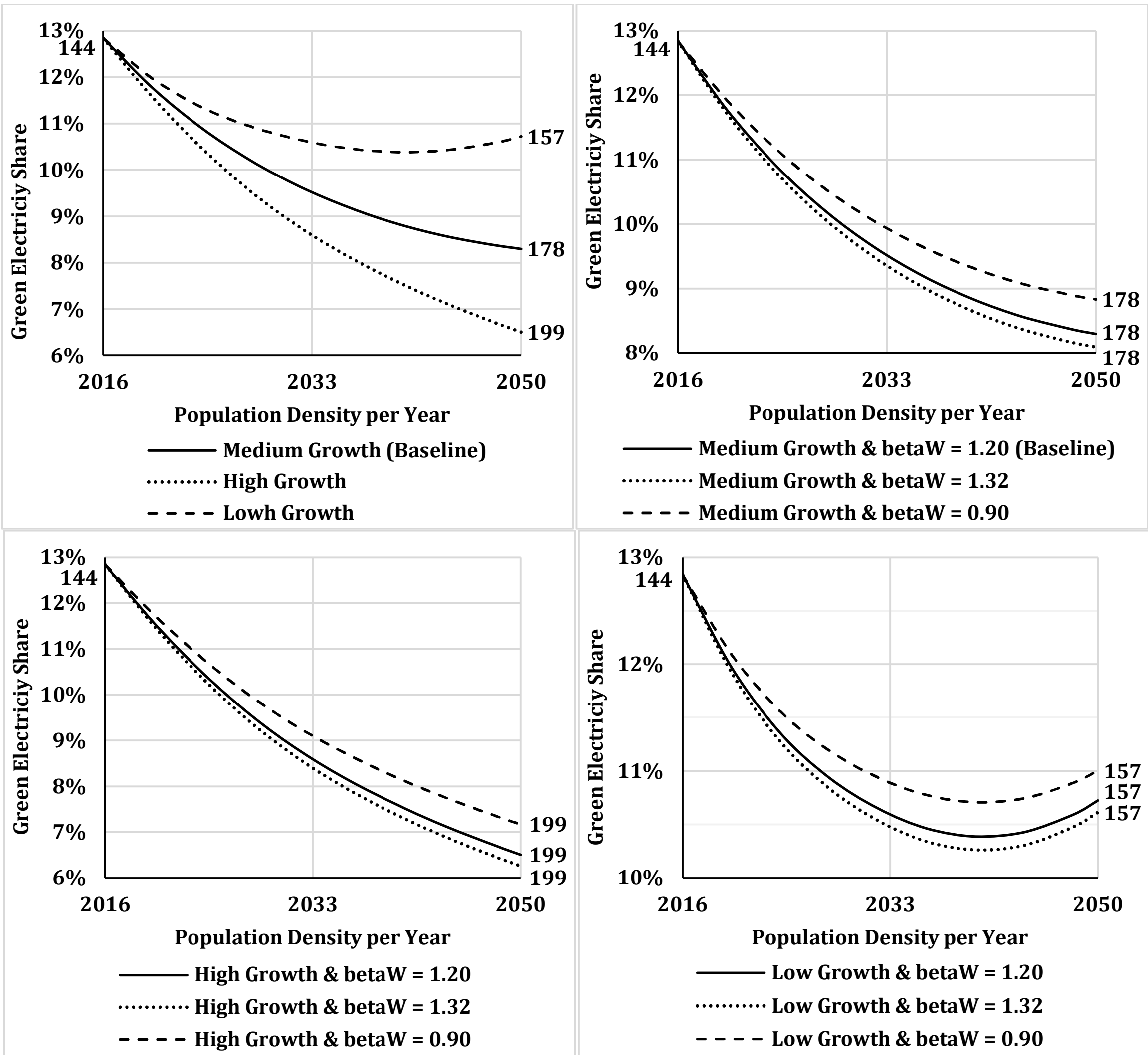


Figure 4.3 shows that, in the medium population growth scenario, the share of green electricity decreases from about 13% in 2016 to about 8% in 2050 (left-hand side). This equals an annual reduction of about 1.24%. Over the same period, the production of green electricity decreases from about 3.5 billion watts in 2016 to 2.8 billion watts in 2050 (see the appendix), which equals a reduction of just over 18.75%. The reduction of the green electricity production is accompanied by a decrease in the green exploitation area, suggesting that there is indeed competition for land between the need for a green exploitation area and other needs, such as residential use. In the high population growth scenario, the share of green electricity drops to about 6% by 2050, corresponding to approximately 2.5 giga watts in production. Interestingly, in the low population growth scenario, the share of green electricity follows a U-curve-shaped pattern, with a minimum around the year 2040. This pattern can be explained by the opposing forces of increasing population density, increasing electricity demand and a relatively low green electricity price because of the relatively low costs of green land area under the influence of a moderate population density.

With adjustments on the intensity of electricity consumption and the effect of the electricity price on the electricity consumption, the bottom part of Figure 4.3 shows that the model outcomes are sensitive to the elasticity of the electricity demand with respect to the population density (β_W). An elasticity of 0.8625 instead of 1.15 (baseline) leads to a 1.07% annual decrease in the share of green electricity (top right-hand side). Figure 4.3 also describes that greater β_W and higher population growth supress the share of green electricity. The impact on the total amount of green electricity is only marginal (see the appendix), implying that the increasing share of green electricity levels out with a relatively moderate increase in the total demand. This underlines the importance of understanding better how agglomeration (increasing population density) influences the demand for energy in general and electricity in particular. In the literature on scaling laws (see, for example, Bettencourt et al., 2007), some evidence has been given for the elasticity of the electricity demand with regard to the population size in cities. In the urban studies literature, some evidence is provided that both increasing urban density and increasing city size reduce households' average energy consumption (see e.g. Glaeser & Kahn, 2010; Larson & Yezer, 2015; Sugahara & Bermont, 2016). The basic idea underlying this so-called compact city argument is that a higher population density makes cities more environmentally friendly because it decreases the average commuting distance and increases the public transport usage, while smaller housing units help to reduce transport and home energy use (Glaeser & Kahn, 2010). However, thus far, the compact city argument has received very little attention in the context of developing countries; exceptions include the studies by Jenks and Burgess (2004), Chen et al. (2008) and Permana et al. (2008).

Figure 4.4 shows that the share of green electricity production increase by about 2 times if the green power density (α_G) increases by 50% (from 200 to 300) and by 2 times if the price elasticity of the green exploitation area with respect to the population density (β_L) decreases by 15%. In contrast, the share and the production of green electricity decrease to about 25% if the green power density (α_G) falls by 50% (from 200 to 100) and even become almost zero if the price elasticity of the electricity exploitation area with respect to the population density (β_L) increase by 15% (to 1.15).

Figure 4.4 – The Share of Green Electricity under the Influence of Changing Population Density (D) and Green Power Density (α_G) (Left) versus the Price Elasticity of the Green Exploitation Area (β_L) (Right)

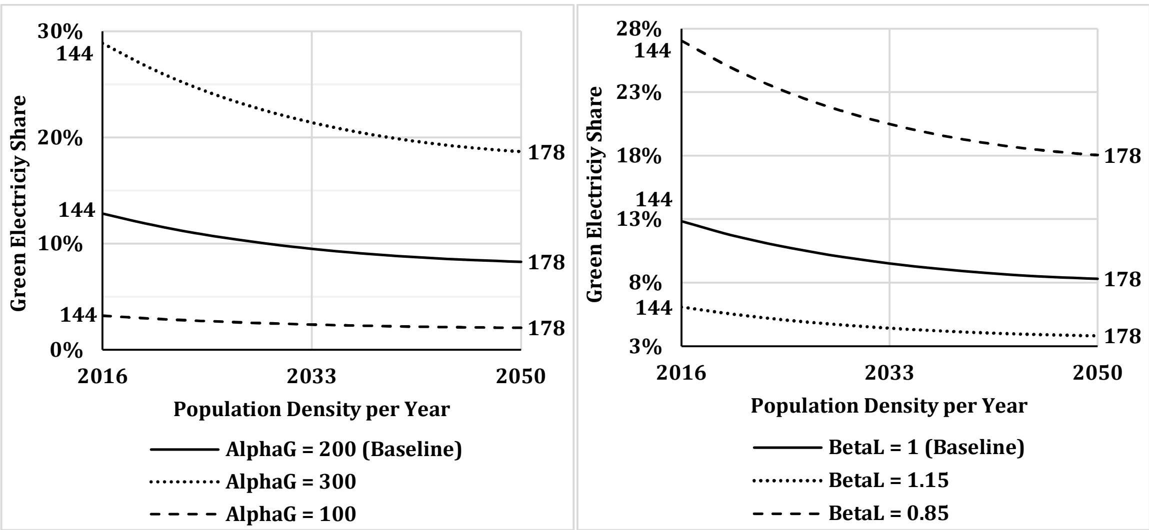


Figure 4.5 – The Share of Green Electricity under the Influence of Changing Population Density (D) and Total Carry Cost (u_B)

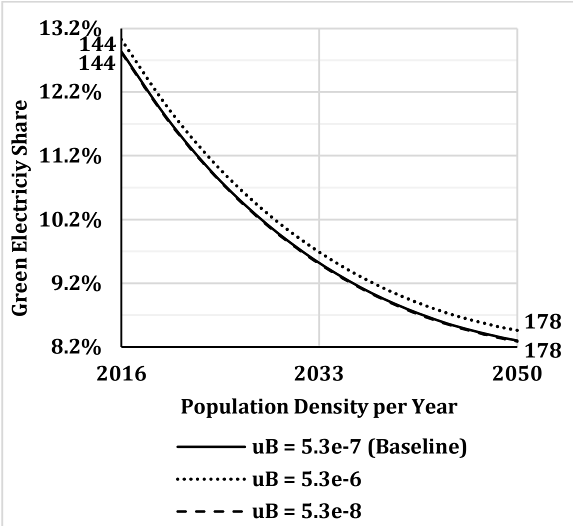
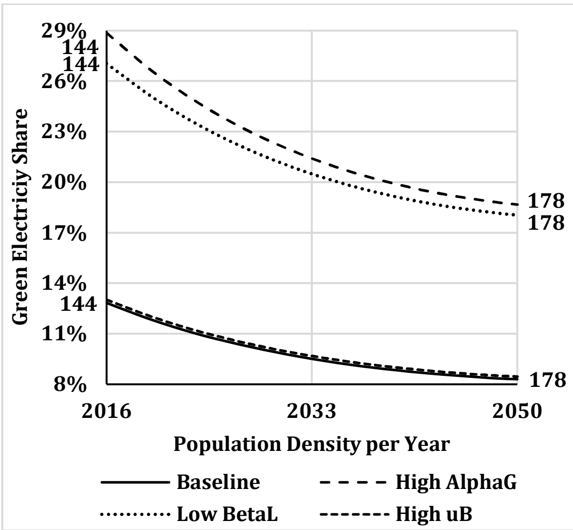


Figure 4.5 indicates that the share of green electricity is not sensitive to the total carry cost of brown resources. They only increase by a small amount when the total carry cost of brown resources (u_B) enhances ten times and even only decrease slightly when the total carry cost of brown resources (u_B) becomes cheaper.

Figure 4.6 – The Share of Green Electricity under the Influence of Changing Population Density (D) and Promoting Green Technology



Note: Promoting green technology: low price elasticity of the green exploitation area, high power density of renewable resources and high total carry cost of non-renewable resources.

Finally, in Figure 4.6, we show the share of green electricity under the promotion of green technology, that is, low price elasticity of the green exploitation area, high power density of renewable resources and high total carry cost of non-renewable resources. The share of green electricity production increase 2 times if the price elasticity of the green exploitation area (β_L) decreases by 15% (from 1 to 0.85) and increase about 2 times if the green power density (α_G) increases by 50% (from 200 to 300). In contrast, a 900% increase in the total carry cost of non-renewable resources (u_B) has almost no impact on the share of green electricity production. The latter can be explained by the already substantial higher power density of brown resources compared with green resources

4.6 Conclusions

Poor access to modern energy and environmental concerns often make developing countries face a dual energy challenge: the simultaneous expansion and greening of their electricity supply. We developed a spatial energy model to analyse the trade-off between greening and brown expansion of the electricity supply in developing countries under the influence of increasing population density. We investigated how the cost advantage of fossil fuels vis-à-vis low-carbon alternatives arises from three interrelated features: geography, power density and technology.

Probably the most prominent feature of spatial transformation in developing countries is increased urbanization. The transition to a predominantly urban society will have a significant impact on the transition to a low-carbon energy system, because there are fundamental physical limits to how much energy we can extract from renewable resources for a given area of land. Fossil fuels are more power dense and hence spatially more productive than renewable energy resources (like solar), which, all things being equal, implies that it is cheaper to transport fossil fuels. If people, because of urbanization processes, are increasingly concentrated in space, the demand for resources with relatively high 'spatial productivity' will increase, thus impeding the emergence of a low-carbon energy system.

Our spatial energy model is a deterministic partial equilibrium model of the electricity supply chain, in which the demand for electricity in a large city can be satisfied by a non-renewable ('brown') energy fuel, a renewable ('green') energy source or both. We found in equilibrium that the level of brown electricity produced increases with the width of the non-renewable exploitation area, the production efficiency of the thermal power plant, the power density of the non-renewable resource, the unit price (or cost) of green electricity, the green transmission losses and the population density. In contrast, the level of green electricity produced increases with the size of the open economy area, the efficiency rate of green power production, the power density of the renewable resource, the unit price (or cost) of brown electricity and the transport costs of the non-renewable resource to the thermal power plant.

We also found that the green electricity price (and thus the level of brown electricity produced) increases with the population size, the share of the total land area devoted to green energy production and the price elasticity of land. On the other hand, the green electricity price (and thus the level of brown electricity produced) decreases with the efficiency rate of green power production, the power density of the renewable resource and the size of the renewable exploitation area.

We calibrated our model to the case of Indonesia. In Indonesia, coal-fired power plants are increasingly satisfying the rising demand for electricity. The country's scattered geography, the associated high costs to transport coal and its relatively 'clean infrastructure slate' may enable the country to exploit quickly a range of low-carbon alternatives. However, we found for Indonesia that the increasing population density over time causes a reduction in green electricity production and thus a falling share of green electricity production in the total electricity supply. We showed that, until 2050, the expected population growth in Indonesia leads to about a 35% reduction of the country's share of electricity produced with renewable energy sources (from 12.8% in 2016 to 8.2% in 2050). This reduction is accompanied by a decrease in the renewable exploitation area, suggesting competition between the need for renewable energy production and other needs, such as residential use. These results are not reversed with a substantially higher assumed power density of the renewable energy sources.

In the context of contemporary spatial dynamics in developing countries, several features of our model deserve further attention in future research. First, as noted in footnote 19, our model could in principle be developed into a full-fledged multi-city model, which certainly is worth the effort once city-specific data on the elasticity of the electricity demand with regard to the population density and on transmission losses are available, to allow for proper calibration of such a model. Second, we argued that the potential renewable exploitation area may become scarcer under the influence of an increasing population density (D) because of the implied increasing demand for residential land. However, it may also be that increased urbanization leads to a decrease in residential land demand, and thus an increase in land suitable for renewable energy production if rural-urban migration increases land availability and an increasing use of smart urban technologies limit the increase in demand for residential land. On the other hand, it is also known that in Indonesia increasing population density not only leads to growth of (mega-)cities but also to increasing sprawl, i.e. growth of the peri-urban area (Statistics Indonesia, 2013) which does decrease the area of land suitable for renewable energy production. Clearly, this issue warrants more empirical research into the spatial evolution of population density.

APPENDIX

Table 4.1 – List of Parameter Values in the Base Simulation

Parameter	Symbol	Value	Unit	Note
The small open economy area	A	1,812	thousand km^2	The land area of Indonesia.
The length of the small open economy	ρ	5,2491.07	km	This value in the model cannot reflect the real distances because, in reality, the width of the small open economy and the exploitation area of the brown resource are different. We set ρ as the distance between Sabang (the northernmost and westernmost city) and Merauke (the easternmost regency).
The power density of the brown resource	α_B	3,297.07	W/m^2	Estimated based on the coal power density in the coal power plant stated by Donald (2016) and the efficiency rate of the thermal power plant (η_B).
The power density of the green resource	α_G	200	W/m^2	Based on the average solar radiation in Indonesia by the Indonesian DGNREEC (2013).
The elasticity of the electricity loss with regard to the population density	β_s	1.1324		Estimated based on the electricity loss in transmission and distribution and the population density of Indonesia during the period 1990–2016.
The elasticity of the electricity demand with regard to the population density	β_W	1.2000		We run several estimations based on electricity consumption and population data at country and city/regency level and the results are between 1.10 and 1.21.
The elasticity of the land price on the green investment cost with regard to the population density	β_L	1.0000		Because we do not have information about the land investment cost for a green power plant, we set this parameter as 1.
The electricity price	p^e	0.6543	\$/W	Based on the average electricity selling price in Indonesia in 2016.
The intensity of electricity consumption	i	1.9524	W/people	This parameter is estimated based on PLN's electricity sales in 2016 (Indonesian MEMR, 2017), the population in 2016 from the World Development Indicators (World Bank, 2017) and β_W.
The maximum intensity of electricity consumption	b	2.8011	W/people	This parameter is estimated based on equation (4.3).
The effect of the electricity price on the electricity consumption intensity	g	1.2970	W^2/(\$·people)	Estimated based on the estimated electricity consumption intensity (i) and the average selling price during the period 2001–2015 in 2016 price.

Table 4.1 – List of Parameter Values in the Base Simulation (continued)

Parameter	Symbol	Value	Unit	Note
The population density	D	144.14	people/km^2	The population density of Indonesia in 2016 from the World Development Indicators (World Bank, 2017).
The effect of the population density on the land price on the green investment cost	θ	2.9987e+7	$/people	This parameter is estimated by deriving a formula based on equations (4.5), (4.22), (4.32), (4.34)–(4.36) and total production and purchasing of electricity generated from green resources by PLN in 2016.
The efficiency rate of the thermal power plant	η_B	30.33%		Based on the average thermal efficiency rate in Indonesia in 2016.
The efficiency rate of the green power plant	η_G	23.83%		Estimated based on the efficiency rate of the solar panel (c-Si type) in 2003 and 2012 and by IRENA (2015) and IEA (2014).
The physical density of the brown resource	f_B	1,075	kg/m^2	Based on the normal weight of coal (145 tons) from a 1 acre area with the thickness of 30 inches by the Kentucky Foundation (2007).
The effect of the population density on the length of the line needed to distribute the electricity	γ	2.5930e+8	kmc·km^2/ people	Estimated based on the estimation for the line length, population density and electricity production of Indonesia in 1999–2014.
The transmission service cost per unit of the line length in the distribution	c	1.2669e+4	$/kmc	It is set so that the TSO profit matches the real data.
The unit investment cost of the thermal power plant	I_B	0.0385	$/W	Based on the estimation of the investment cost of a coal steam power plant in Indonesia in 2016 prices per year of lifetime from some sources.
The maximum unit investment cost of the green power plant	I_G^k	0.0746	$/W	Based on the investment in a solar power plant by IRENA (2016) in the 2016 price per year of lifetime.
The share of the green exploitation area	ψ_G	4.0390e–5		Estimated based on estimated by deriving a formula based on equations (4.5), (4.22), (4.32), (4.34)–(4.35) and total production and purchasing of electricity generated from green resources by PLN in 2016.
The effect of the length of the line on the transmission and distribution loss	τ	1.0179e–8	%/mc	Estimated based on the electricity loss in the transmission and distribution and the total length of lines of low, medium, high and extra high voltage of Indonesia in 2016.

Table 4.1 – List of Parameter Values in the Base Simulation (continued)

Parameter	Symbol	Value	Unit	Note
The unit delivery cost of the brown resource	u_B	0.5328	\$/ton·km	Based on the coal transport cost in Indonesia in 2016. Price by IDOMINING (2016).[31]
The elasticity of the transmission service cost with regard to the total carry cost	δ	1.1		δ is set so that δ > 1.
The production rate in the thermal power plant	z_B	49.14%		Estimated based on the installed capacity and the electricity production of thermal and green power plants of Indonesia during the period 2001–2016.
The production rate in the green power plant	z_G	100.00%		The green production is assumed to be at full capacity.

Notes: (1) All monetary values are converted into prices in 2016. (2) kmc = km circuit.

[31] Our reference shows that coal is distributed to the power plant by a train or barge and that the total carry cost of the train is more expensive than the total carry cost of the barge.

Table 4.2 – The Result of the Base Simulation to Obtain W_B^e and W_G^e that Maximize Π_T^e

Parameters and Exogenous Variables

Unit	Parameter	Value
km^2	A	1.8116E+06
km	ρ	5.2491E+03
W/m^2	α_B	3.2971E+03
W/m^2	α_G	2.0000E+02
	β_s	1.1324E+00
	β_W	1.2000E-00
$/W	p^e	6.5434E-01
$/people	b	2.8011E+00
W^2/$·people	g	1.2970E+00
W/people	i	1.9524E+00
$people/km^2$	D	1.4414E+02
$/people	θ	2.9989E+07
	β_L	1.0000E+00
	ψ_G	4.0390E-05
	η_B	3.0330E-01
	η_G	2.3834E-01
kg/m^2	f_B	1.0749E+03
$kmc.people/km^2$	γ	2.5930E+08
kmc	s	9.3131E+05
$/W	I_B	3.8466E-02
$/W	I_G^k	7.4626E-02
km	λ	0.0000E+00
	L	9.4800E-02
mc	s	9.3131E+08
$/kmc	c	1.2669E+04
/mc	τ	1.0179E-10
$/kgm	u_B	5.3284E-07
	δ	1.1000E–00
kW	W_D^e	2.4591E+10
	z_B	4.9137E-01
	z_G	1.0000E+00
km	ω	3.4512E+02
$\$/m^2$	I_G^L	4.3223E+03
people	N	2.6112E+08
$/W	I_G	7.8288E-02
$/W	p_G^e	7.8288E-02

Endogenous Variables

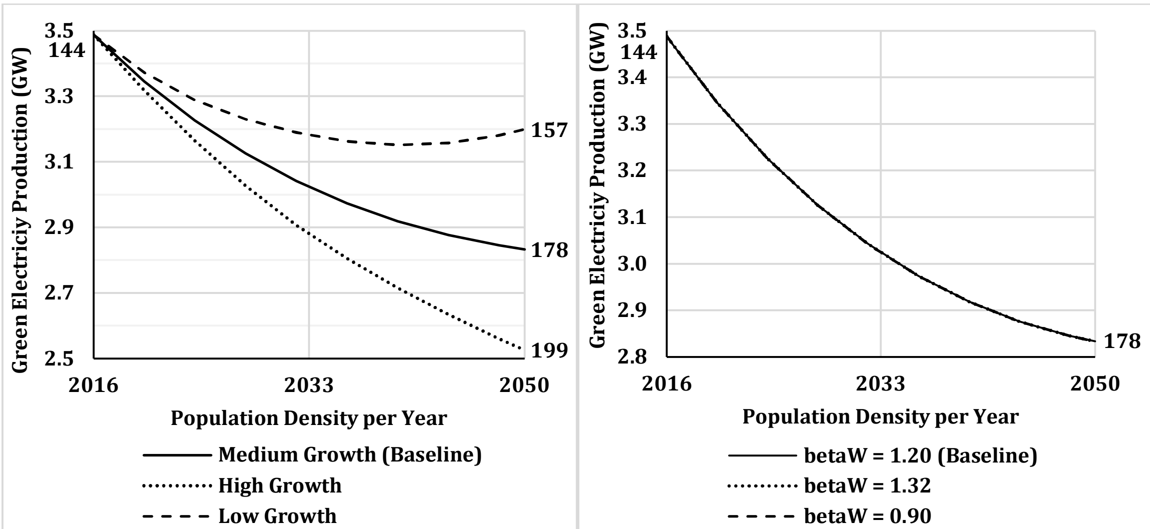
Unit	Variable	Value
m^2	A_B	2.3679E+07
m^2	A_G	7.3169E+07
W	k_B	4.4190E+10
W	k_G	3.4878E+09
$/W	p_B^e	7.8288E-02
$/W	p_B^m	1.4056E-06
M	r_B	6.8610E+01
$	Π_B^e	0.0000E+00
$	Π_G^e	0.0000E+00
$	Π_B^m	0.0000E+00
$	Π_T^e	1.1651E+10
W	W_B^e	2.3679E+10
W	W_B^m	7.8070E+10
W	W_G^e	3.4878E+09
W	W_G^r	1.4634E+10
W	W_S^e	2.4591E+10
kg	x_B	2.5452E+10

Table 4.3 – Comparison of the Basic Simulation Result with Real Data

Variable	Unit	Simulation	Difference	Data in 2016	Note
W_S^e	W	2.7167E+10	−4.182%	2.8303E+10	Based on data in 2016
W_B^e	W	2.3679E+10	−5.077%	2.4814E+10	
W_G^e	W	3.4878E+09	−0.019%	3.4885E+09	
L	%	9.4800	0.000%	9.4786	
s	mc	9.3131E+08	0.000%	9.3131E+08	
Π_T^e	$	2.1651E+09	−0.043%	2.1651E+09	
k_B	W	4.8190E+10	−9.099%	5.2574E+10	
k_G	W	3.4878E+09	−103.507%	7.0984E+09	

Notes: (1) The data in 2016 are from the Indonesian Ministry of Energy and Mineral Resources and PLN. (2) The unit measurement in Wh is converted into W, where hours in year t = number of days in year t × 24 hours/day. (3) The simulation is based on the assumption that the production rate of the green power plant is at full capacity. In reality, the production is not at full capacity. (4) The huge difference for k_G is because, in our model, we assume that the rate of production in the green power plant is 100%, while, in reality, it is not.

Figure 4.7 – The Production of Green Electricity under the Influence of Changing Population Density (D) (Left) versus Elasticity of the Electricity Demand with Respect to the Population Density (β_W) (Right)



CHAPTER 5 The Impact of City Size and Population Density on Residential Energy Use in Indonesian Cities

5.1 Introduction

In a few decades from now, the world's urban population will be larger than the current entire global population. This clustering of people and firms in urban areas causes cities to act as engines of local, national and global economic growth. However, urbanization also has a substantial influence on the global energy consumption and therefore on emissions. In 2013, around 53% of the world's population lived in urban areas. These areas were responsible for 64% of primary energy use and 70% of CO_2 emissions in the world (IEA, 2016). As such, patterns of urbanization can be expected to play a key role in future global environmental change. Traditionally, rich countries were largely responsible for global emissions and energy, but nowadays both urban and GHG emission growth are largely driven by countries in the global South (IEA, 2010; Jakob et al., 2014). Of course, this can be explained by the fact that the processes of urbanization and economic change nowadays are much faster in developing countries than in the developed world. Until 2050, around 90% of global urban population growth will take place in developing countries, and, by 2050, around 80% of the total urban population is expected to live in cities in the global South (United Nations, 2015).

Still, most of the existing literature on the interaction between energy use and urbanization has focused on countries in the Western world (e.g. Glaeser & Kahn, 2010; Larson & Yezer, 2015). The available research on energy use in developing countries has largely ignored the spatial structure of economic development (e.g. Badruzzaman, 2013; Chen et al., 2013; Wijaya, 2013; Liu et al., 2015; Permana et al., 2015; Sukarno et al., 2015). This chapter aims to contribute to the literature by analysing the spatial dimensions of the interaction between energy use and urbanization in Indonesia, a large country in the global South with more than 260 million inhabitants.

More specifically, we first investigate whether urbanization influences the per capita energy consumption, controlling for the impact of urbanization on per capita incomes. To achieve this aim, we develop an instrumented 2-stage regression method, which we apply to a cross-city dataset for 71 Indonesian cities that was constructed from existing household surveys and census data. In addition, we analyse the spatial patterns of energy consumption across districts within the metropolitan area of Yogyakarta, one of Indonesia's largest cities. We conducted a survey on energy consumption and travel behaviour among 748 households in Yogyakarta Province. The individual dimension of the survey data allows us to evaluate the extent to which the observed impact of urban indicators on energy consumption is influenced by the spatial sorting of people across districts in Yogyakarta Province. We use an estimation strategy that is inspired by the approach that Combes et al. (2008) developed to control for worker heterogeneity in explaining spatial wage disparities across local labour markets in France.

An important finding in the literature on the relationship between urban form and energy use is that both increasing urban density and increasing city size reduce households' average energy consumption (see e.g. Glaeser & Kahn, 2010). The basic idea underlying this so-called compact city argument is that a higher population density makes cities more environmentally friendly, because it decreases the average commuting distance and increases the public transport usage, while smaller housing units help to reduce transport and home energy use. This confirms earlier findings that the population density and degree of urbanization are inversely related to vehicle energy consumption in developed countries (cf. Liddle, 2004; Brownstone & Golob, 2009; Makido et al., 2012). However, to the best of our knowledge, this line of argument has not been tested in the context of developing countries, in which the involved mechanisms may lead to different outcomes, especially in countries that combine low incomes and rapid urbanization. For example, urbanization in developing countries may cause people to substitute away from relatively inefficient fuel consumption – like kerosene or traditional biomass – and to adopt vehicles and electricity appliances with higher energy efficiency.

The organization of this chapter is as follows. In section 5.2, we provide a literature review in which we discuss the various factors that may influence urban energy use. In section 5.3, we present our datasets and a brief descriptive analysis of the key correlations. In sections 5.4 and 5.5, we present the regression analyses that make use of, respectively, the cross-city and within-city datasets. Section 5.6 concludes.

5.2 Literature

The literature on the impact of urbanization on energy use and emissions presents a mixed picture. Some studies have concluded that the urban population has a positive impact on energy consumption or CO_2 emissions (Jafari et al., 2012; Poumanyvong et al., 2012), caused by the development of industries in urban areas, the high intensity of transport activities, which is encouraged by a good road infrastructure (especially if there is no good public transportation), and the declining of green zones in urban areas (Burgalassi, 2010; Abouie-Mehrizi et al., 2012; Jafari et al., 2012). Martinez-Zarzoso and Maruotti (2011), however, found an inverted U-shaped relationship between urbanization and CO_2 emissions in low, middle-low and upper-middle income countries. The quadratic relationship represents the Environmental Kuznets Curve (see Chapter 2), indicating that continued urbanization might lower the CO_2 emissions once the maximum level of emissions is reached, for example because, at higher levels of urbanization, people shift towards more environmentally friendly vehicles and increasing household energy efficiency. Still other studies have shown that areas with a larger population size or higher population density tend to have lower per capita energy consumption or emissions (Newman & Kenworthy, 1989; Banister et al., 1997; Chen et al., 2008; Ewing & Rong, 2008; Glaeser & Kahn, 2010).

Especially the study by Glaeser & Kahn (2010) – who found for cities in the United States that the population size has a negative statistically significant impact on the total emissions from all types of energy on energy consumption (emissions) from private transportation and on emissions from electricity – has given rise to the idea that high population density makes cities more environmentally friendly (Dieleman & Wegener, 2004; Mindali et al., 2004; Neuman, 2005). However, this so-called compact city concept as a sustainable urban form is subject to debate, because some studies have found non-negative relationships between population size or population density on the one hand and energy consumption or emissions on the other hand. For example, Mindali et al. (2004) discovered a negative correlation between energy consumption for transport and urban density for a range of European cities, but they found no correlation between energy consumption for transport and urban density in cities in the United States and Australia. Fragkias et al. (2013) found, for a sample of US metropolitan areas during the period 1999–2008, that CO_2 emissions scale proportionally with the urban population size, thus concluding that larger cities are no more emission efficient than smaller ones.

The ability of a compact city to decrease energy consumption or emissions could also be questioned in the context of developing countries, for example because urbanization patterns in developing countries are very fast in today's developing world (taking roughly half the time of historical urbanization processes in Europe) and because cities in developing countries might follow a different economic and social development trajectory and are different culturally and in terms of the environmental challenges that they face (Jenks & Burgess, 2004; Chen et al., 2008). The relationship between urban form and energy use in developing countries therefore does not necessarily need to resemble that in rich countries. So far, the evidence on the relationship between urban form and energy consumption or emissions comes almost exclusively from developed countries. In Indonesia, many studies have investigated energy consumption, but only a few studies have related energy consumption to urban form (Permana et al., 2008; Astinawaty & Kustiwan, 2013; Badruzzaman, 2013; Wijaya, 2013; Andadari et al., 2014; Permana et al., 2015; Sukarno et al., 2015). To the best of our knowledge, this study is the first that explicitly investigates the effects of urbanization in general and compact areas on energy consumption in Indonesia.

From the literature, it is safe to conclude that the population density alone is not sufficient to guarantee a decrease in the per capita energy consumption or emission reductions. Some studies have argued that urban land use must be multi-purposed to reach those goals, for example through developing multi-family housing instead of single-family housing (Neuman, 2005; Ewing & Rong, 2008). In addition, residential locations must be close to facilities such as schools and shopping centres to encourage people to reach those facilities by walking or cycling (Dieleman & Wegener, 2004; Mindali et al., 2004; Neuman, 2005). Workplaces ought to be centralized in only a few locations, which are integrated with a good, cheap public transportation system so that people will be motivated to use public transportation instead of private transportation (Dieleman & Wegener, 2004; Mindali et al., 2004; Neuman, 2005; Burgalassi, 2010). Larson and Yezer (2015) developed a model to simulate the impact of doubling the city size on the energy consumption in the United States. Their simulation showed, among other results, that the energy consumption per household reduces significantly when urban growth is driven by improved amenities and will not change much when urban growth is driven by higher wages that are induced by agglomeration economies.

Urbanization, Growth and Energy Use

Urbanization could also be related to energy consumption through economic growth. A higher income as well as the better facilities that accompany economic development – such as schools, hospitals, shopping centres, cultural events, etcetera – might encourage people to move from rural area to urban areas. The higher population density caused by urbanization will result in large product and labour markets. It will attract producers to open their business in urban areas, improve the attractiveness of urban areas and increase the per capita income in urban areas (UNCHS Habitat, 1994; Bloom et al., 2008).

The effect of economic development or increased income on energy consumption or emissions could be positive as well as negative. When urbanization causes a transition from the agricultural sector to the manufacturing sector (Moomaw & Unruh, 1997; De Groot, 1999), it will increase the energy consumption and emissions (Jafari et al., 2012; Poumanyvong et al., 2012). However, when urbanization causes a transition from the manufacturing sector to the service sector (Moomaw & Unruh, 1997; Glaeser & Kahn, 2010), it may decrease the energy consumption and emissions. For a sample of OECD countries, Mulder et al. (2014) indeed found that the shift towards a service economy has contributed to lower overall energy intensity levels. However, controlling for this trend, the impact of structural changes within the service sector has been found – by means of a decomposition analysis – to increase the energy intensity levels over time in about one-third of the OECD countries.

Urbanization and Lifestyle

Urbanization also impacts energy use and emissions through changes in lifestyle and personal consumption. Higher incomes in urban areas, driven by agglomeration economies, will enable people to consume more energy for dwelling such as to enjoy air conditioning or more home entertainment using electronic devices and to consume energy for more travel. Some studies found evidence that income has significant positive effects on energy use for or emissions from a dwelling (Ewing & Rong, 2008; Wijaya, 2013; Andadari et al., 2014). Furthermore, urban development could drive the improvement of the transportation network. If the infrastructure for a private vehicle becomes better and public transportation is not well developed, then it will encourage more private vehicle uses (Burgalassi, 2010). Some studies discovered that people with higher income tend to consume more energy for or emissions from transport (Permana et al., 2008; Glaeser & Kahn, 2010; Poumanyvong et al., 2012; Astinawaty & Kustiwan, 2013; Permana et al., 2015). On the other hand, when people's welfare increases, they attach larger value to a better environment and they may also invest more in advanced technology which can subsequently reduce the energy consumption and emissions (Moomaw & Unruh, 1997; De Groot, 1999; Smulders et al., 2011).

Urbanization and Travel Distance

A crucial spatial factor that determines the relationship between urbanization and energy use is travel distance. Usually, there is a negative correlation between the distance from a household's residential location to the city center and population density (Muniz & Galindo, 2005; Larson & Yezer, 2015). According to the bid-rent model by Alonso (Neuman, 2005), economic agents will choose a location which they can afford. Larson & Yezer (2015) in their simulation showed that distance of household residence from the city center has a negative relationship with house prices and land rents. Thus, in countries where multi-family houses are well developed, poor households live in multi-family houses around the city center and rich households live in single-family houses in the suburban areas (Neuman, 2005). Conversely, in countries where most households occupy single-family homes, poor families live in the suburban area and rich families live around the city center. If most facilities and jobs are available in the city center then households living in suburban areas will have a longer commute (Mindali et al., 2004; Ulfa & Suwandono, 2014). Obviously, commuting distance will have a positive effect on energy consumption for transport. For example, Banister et al. (1997) showed for the United Kingdom that trip length has a positive highly significant correlation with energy consumption for transport. If the road network between areas is good and public transport connections are poor, then people will be provoked to ride private motor vehicles increasing energy consumption for transport. Even when public transportation services are good, they are oftentimes relatively expensive so that people still find it economically attractive to use a private vehicle. This might explain why motorcycle use is so high in Asian countries (Hsu et al., 2003; Senbil et al., 2007).

Commuting distance may also have an influence on energy consumption for dwellings since long commutes reduce the time spent at home (and thus the energy use at home). This effect has been found for Indonesia by Wijaya (2013), who discovered that the duration time spent at home has a significantly positive effect on the electricity bill in Bandung City and Denpasar City, while in Yogyakarta City, the effect was found to be significantly negative. Wijaya (2013) argues that the negative effect found in Yogyakarta is because households in Yogyakarta City prefer to spend time together when they are at home rather than doing activities using electronic devices individually. Although we are not aware of studies that investigated the effect of commuting distance on energy consumption for cooking, we consider that the time spent at home could also influence the energy consumption for cooking, because lack of time has been reported as an obstacle to preparing food (Larson et al., 2006) and lack of time for cooking could be caused by a long travel time. In the United States, many people do not cook and eat their meals at home, but instead choose to buy meals, especially with the development of fast food outlets (Schipper et al., 1989). Smith et al. (2013) found evidence in the United States that the time spent to prepare food in 1965-1966 was higher than in 2007-2008. The same phenomenon was found in South Africa. Commuters with a long travel distance tend to bring snacks or food that can easily be prepared and does not need a long cooking time (Bourne et al., 2002).

Household Composition

Households' energy consumption for dwellings will also be influenced by the number of household members (IEA, 2014). Preparing food for small or big household sizes might not differ too much in terms of energy consumption for cooking. Nonetheless, to reduce their expenditures, large families could encourage household members to use energy more efficiently by, for example, sharing the usage of the motor vehicle or sharing electrical appliances. In the United Kingdom, Banister et al. (1997) found a positive correlation between household size and energy consumption for transport in the Merseyside conurbation but discovered a negative correlation in Banbury. In the United States, Glaeser & Kahn (2010) showed that households' size has a significantly positive effect on their annual total gasoline consumption. In Indonesia, Wijaya (2013) discovered that family size has a positive significant influence on households' electricity bill in Bandung City, Denpasar City and Yogyakarta City, whereas Andadari et al. (2014) found that household size has no effect on LPG use but a significantly positive effect on LPG expenditure in Semarang Regency and Salatiga City.

Finally, the house size or the floor area of the household residence will also affect the energy consumption for dwellings (IEA, 2014). The house size can represent the need for energy for lighting and fans, air conditioners or heaters. There is some empirical evidence that the floor area of the household residence has a positive effect on the energy consumption for electricity (Ewing & Rong, 2008; Wijaya, 2013).

In the remainder of this chapter, we assess whether urbanization influences per capita energy consumption beyond the indirect impact occurring through the per capita income for cities in Indonesia. Inspired by the literature summarized above, we develop an instrumented two-stage regression method, in which we control for the role of schooling levels, density, city size, commuting distance, household size and house size in determining urban energy consumption.

5.3 Data and Summary Statistics

We assess the impact of urbanization and urban form (i.e. urban density) on the per capita energy use in Indonesia at two levels of aggregation. First, we assess the determinants of per capita energy use across a sample of 71 Indonesian cities. Second, we do so for 748 households within cities in Yogyakarta Province. In our cross-city analysis, we use a dataset that was constructed from existing household surveys and census data. In our within-cities analysis, we use data that we collected through a survey on energy consumption and travel behaviour in Yogyakarta Province, one of the provinces in Java Island, the most populated island in Indonesia. Table 5.1 displays the demographic characteristics of our two samples: cities across Indonesia and districts across the Yogyakarta Metropolitan Area. See Tables 5.10 and 5.11 in the Appendix for the full list and characteristics of the involved cities and districts.

Table 5.1 – Demographic Characteristics of Our Samples: Cities in Indonesia and Districts in the Yogyakarta Metropolitan Area

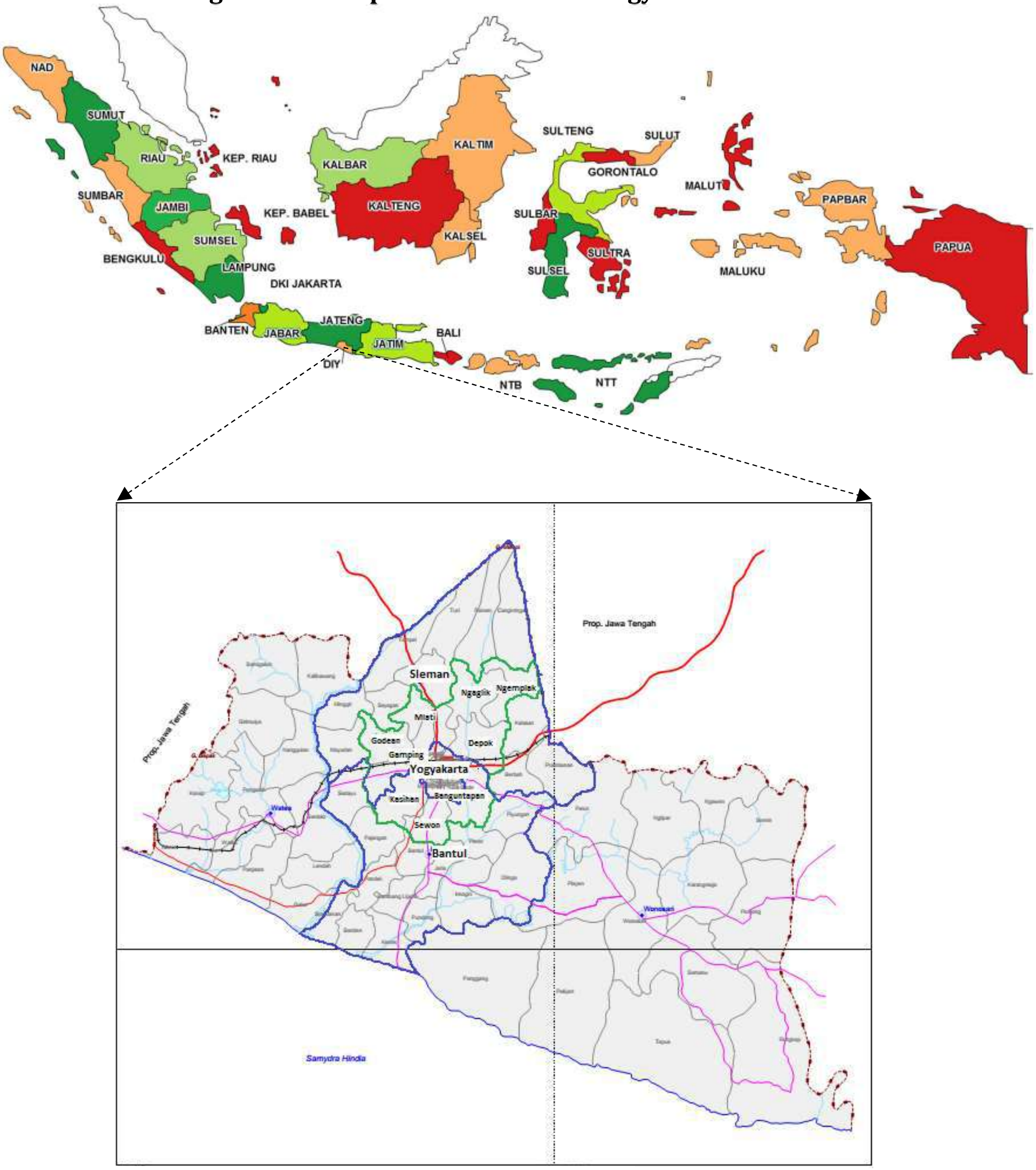
		Population	Area	Density	Annual Population Growth
		1,000 People	km^2	People/km^2	%
Cities in Indonesia(1)	Year	**2012**	**2012**	**2012**	**2000–12**
	Mean	839.2	2,117	3,532	1.56
	Min.	85.5	11	4	–6.92
	Max.	9,862.0	46,792	14,890	7.58
	N	71	71	71	71
Districts in Yogyakarta Metropolitan Area(2)	Year	**2016**	**2016**	**2016**	**2000–16**
	Mean	54.7	22	5,842	1.0
	Min.	9.3	1	794	–0.8
	Max.	188.8	54	20,649	2.9
	St. Deviation	37.7	15	5,875	1.0
	N	48	48	48	48
Yogyakarta City(3)	N=14	418	32.5	12,854	0.32
Sleman Regency(3)	N=17	1,180	574.8	2,054	1.69
Bantul Regency(3)	N=17	983	506.9	1,940	1.45

Notes: (1) The population in 2012 is from the Indonesia Database for Policy and Economic Research (World Bank, 2015); the area in 2012 and population in 2000 are from the Indonesia Database for Policy and Economic Research (World Bank, 2015) and various official statistical reports of cities, regencies and provinces in Indonesia. (2) The population and area in 2016 are from the Statistics of Bantul Regency (2017), Statistics of Sleman Regency (2017) and Statistics of Yogyakarta Municipality (2017), whereas the population in 2000 is from the census (Statistics of D.I. Yogyakarta, 2001a, 2001b, 2001c). (3) The population and area in 2016 are from the Statistics of D.I. Yogyakarta Province (2017) and the population in 2000 is from the Statistics of D.I. Yogyakarta Province (2005).

For our cross-city analysis, we employ data from various sources. We use the BPS living cost survey in 2012 (BPS, 2013a, 2013b, 2013c) to collect data on energy use. This survey is conducted every 5 years in urban areas (BPS Indonesia, 2011) and covers 82 cities: 33 capital cities of provinces and 49 big cities or regencies in Indonesia, which are well developed and absorb many workers (BPS Kabupaten Aceh

Barat, 2016).[32] Because of the limited data availability for 11 of these cities, our dataset includes 71 cities.

Figure 5.1 – Map of Indonesia and Yogyakarta Province



Notes: Yogyakarta is known as DIY Province. The blue line marks the border of Yogyakarta City, Sleman Regency and Bantul Regency, and the green line shows the border of districts in Yogyakarta Urban Agglomeration Area.
Source: The map of Yogyakarta Province is from Dinas PUP-ESDM DIY (2015), and the map of Indonesia is from https://www.pinterest.com.au/pin/672936369293684236/

[32] In regencies, the living cost survey was conducted in the capital city of the regency, which usually consists of one or more districts in the regency. In the case that the complementary data (area, population, number of households, GDP and mean years of schooling of the population aged 15 years or older) were not available for the capital city of the regency, we substituted them with data from the regency, assuming that data from the living cost survey are representative of the regency.

The survey in Yogyakarta Province was conducted in February 2016. We surveyed in total 826 households in urban and rural areas in Yogyakarta City, Sleman Regency and Bantul Regency (Figure 5.1). We did not survey households in Kulon Progo Regency and Gunung Kidul Regency.

We chose Yogyakarta City, Sleman Regency and Bantul Regency because of their urban character, defined in terms of a relatively high population density and per capita GRP. We were able to collect household data from more than 95% districts in the research area; this wide coverage in terms of districts helps us to capture commuting behaviour relatively good. Because we decided to focus on analysing energy use in urban areas, and due to missing data, we were left with 748 households in our final dataset (see Table 5.2). This sample size is almost double the minimum sample size that must be collected according to Stovin's formula with 5% margin of error (Ryan, 2013).[33]

Table 5.2 – Number of Households and Sample Size of the Yogyakarta Survey

	Yogyakarta	Sleman	Bantul	Total
Population[1)]	128,873	281,363	213,626	623,862
Sample	151	380	217	748

Note: The number of heads of household in the urban area in semester 2 of 2015.
Source: Population and Civil Registration Office (Biro Tapem Setda DIY, 2015).

The key variables in our analysis are per capita residential energy use, population size, population density, education and historical urban population, whereas the control variables are per capita income and household size. Across cities, we measure energy use as the average monthly household energy expenditure on energy. Energy expenditure includes expenditure on electricity use, energy for cooking and gasoline and diesel fuel for private vehicle use. The GRP in 2012 was taken from the Indonesia Database for Policy and Economic Research (World Bank, 2015).[34] Using the household energy expenditure, population and number of households data, we calculated the per capita energy expenditure data, and, using income (GRP) and population data, we calculated the per capita income. Next, we converted the energy

[33] Minimum $n = \frac{N}{(1+N \cdot e^2)} = \frac{623{,}862}{(1+623{,}862 \cdot 5\%^2)} = 399.74 \approx 400.$
[34] GRP including oil and gas.

expenditure and income data into international dollars.[35] The data on the population size per city, area size, number of households and mean of years of schooling (of the population aged at least 15 years old in 2012) were taken from the Indonesia Database for Policy and Economic Research (World Bank, 2015) and reports published by the Central Bureau of Statistics and the Health Department in Indonesia.

In Yogyakarta, we collected data at the household level on the energy consumption, household income, household size, average education level attained by household members,[36] average commuting distance and house size. Energy use is measured as the quantity consumed per month and includes energy consumption for (private and public) transport, electricity and cooking. As in our cross-city dataset, we converted household-level data on energy consumption and income into per capita energy consumption and per capita income, which we then converted into international dollars.

The average commuting distance is defined as the one-way travel distance from a household's residence to the location of the main activity of a household member – assuming that he or she travels the same way when returning. In the survey, a commuter is defined as a household member who regularly travels to the location of his main activity, such as work, study, shopping and so on, and then returns home within 24 hours. The questionnaire of the survey is presented in Appendix C.

We also employ data on the distance from households' residence to the city centre. To this aim, we identify the Malioboro region in Yogyakarta as the city centre. Typically, the city centre – also known as the urban core, the CBD (central business district) or the civic centre (Damayanti & Handinoto, 2005) – is the area in a city where one can find a concentration of political power, cultural manifestations, business and financial services, shopping facilities and entertainment. Sometimes it has clear historical roots. The Malioboro region is home to the office centre of the Governor of Yogyakarta Province, the branch office of the Central Bank of Indonesia, the biggest traditional market in Yogyakarta, named Beringharjo, and the historic Vredeburg Fortress. Furthermore, Malioboro is the famous tourism region of Yogyakarta and is near Yogyakarta Palace, an important symbol of Javanese culture.

[35] All data in money value were converted into international dollars based on the conversion rate from Quandl for 2012, which was retrieved from https://www.quandl.com/data/ODA/IDN_PPPEX-Indonesia-Implied-PPP-Conversion-Rate-LCU-per-US on 25 December 2015.

[36] Codes for education level in the survey: 1 = no schooling, 2 = not completed elementary school, 3 = elementary school, 4 = junior high school, 5 = senior high school, 6 = diploma I/II, 7 = diploma III, 8 = diploma IV/bachelor's degree and 9 = master's/doctoral degree.

Malioboro has been referred to as the city centre by other researchers (Damayanti & Handinoto, 2005; Sugiyanto et al., 2011; Utari, 2015). The distance between a household's residence and Malioboro was estimated using Google Maps and the respondent's address.

The total population and area by district (in 2016, the year when the survey was conducted) were taken from the Statistics of Yogyakarta Municipality (2017), Statistics of Sleman Regency (2017) and Statistics of Bantul Regency (2017). The urban population in 2000 is from the 2000 population census in Yogyakarta City, Sleman Regency and Bantul Regency (BPS Provinsi DIY, 2013). The total population, population density and historical urban population represent data in the district where a household is located.

Tables 5.3 and 5.4 display the correlation coefficients between the key variables from our cross-city and cross-district datasets in Indonesia and Yogyakarta Province, respectively, along with their summary statistics. For the cross-city dataset in Indonesia, they are the per capita total energy expenditure (*TOENEXPCAP*), per capita energy expenditure on transport (*TRANEXPCAP*), per capita energy expenditure on dwellings (*DWELEXPCAP*), mean of years of schooling of the population aged 15 or older (*EDU*), historical urban population (*URBAN*), per capita income (INCCAP), population density (*DENSITY*), city size (*POPULATION*) and household size (*HHSIZE*). For the cross-district dataset in Yogyakarta Province, they are the per capita total energy quantity (*QTOENCAP*), per capita energy quantity for transport (*QTRANCAP*), per capita energy quantity for dwellings (*QDWELCAP*), average education level attained by household members (*EDU*), historical urban population (*URBAN*), per capita income (*INCCAP*), population density (*DENSITY*), city size (*POPULATION*), distance between the household's residency and the city centre (*CBD*), average commuting distance (*DISTANCE*), household size (*HHSIZE*) and house size (*FLOOR*).

Table 5.3 – Correlation and Summary Statistics across Cities in Indonesia

	LNEXPTOENCAP	*LNEXPTRANCAP*	*LNEXPDWELCAP*	*EDU*	*LNURBAN*	*LNINCCAP*	*LNDENSITY*	*LNPOPULATION*	*HHSIZE*
LNEXPTOENCAP	1.0000								
LNEXPTRANCAP	0.8262 ***	1.0000							
	(0.0000)								
LNEXPDWELCAP	0.8683 ***	0.4504 ***	1.0000						
	(0.0000)	(0.0000)							
EDU	0.2397 **	0.1651	0.2329 **	1.0000					
	(0.0301)	(0.1382)	(0.0352)						
LNURBAN	0.4581 ***	0.5326 ***	0.2862 **	0.3385 ***	1.0000				
	(0.0001)	(0.0000)	(0.0155)	(0.0039)					
LNINCCAP	0.3768 ***	0.4384 ***	0.2096 *	0.3431 ***	0.3916 ***	1.0000			
	(0.0005)	(0.0000)	(0.0587)	(0.0016)	(0.0007)				
LNDENSITY	0.1984 *	0.3091 ***	0.0489	0.4750 ***	0.6965 ***	0.2710 **	1.0000		
	(0.0740)	(0.0047)	(0.6624)	(0.0000)	(0.0000)	(0.0138)			
LNPOPULATION	0.4732 ***	0.5536 ***	0.2922 ***	−0.0600	0.8212 ***	0.3196 ***	0.3956 ***	1.0000	
	(0.0000)	(0.0000)	(0.0077)	(0.5922)	(0.0000)	(0.0034)	(0.0002)		
HHSIZE	−0.5383 ***	−0.3549 ***	−0.5436 ***	0.1963 *	−0.1867	0.0096	0.0058	−0.2316 *	1.0000
	(0.0000)	(0.0011)	(0.0000)	(0.0771)	(0.1191)	(0.9321)	(0.9586)	(0.0363)	
Unit	Int. $/month	Int. $/month	Int. $/month	years	people	Int. $/year	people/km^2	people	people
Observation	82	82	82	82	71	82	82	82	82
Mean	3.1182	2.1921	2.5899	9.1973	12.4958	8.7776	7.0697	13.0077	4.0370
St. Deviation	0.2602	0.3864	0.2609	1.6412	1.1665	0.6607	1.7848	0.9538	0.5600
Minimum	2.5147	1.1312	2.0044	4.4800	9.2739	7.4507	1.4816	11.0366	3.0039
Maximum	3.7529	2.9742	3.3344	12.0700	15.9391	11.2166	9.6084	16.1042	6.4112

Notes: LN = natural logarithm, EXP = expenditure, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwelling, EDU = mean of years of schooling of population aged at least 15, URBAN = historical urban population, INC = income, DENSITY = population density, POPULATION = city size and HHSIZE = household size. For the variable URBAN, we only have 71 observations because some contemporary cities were not yet formed in 2000.

Table 5.4 – Correlation and Summary Statistics across Households in Yogyakarta Province

	LNQTOEN CAP	*LNQTRAN CAP*	*LNQDWEL CAP*	*EDU*	*LNURBAN*	*LN INCCAP*	*LN DENSITY*	*LNPOPU-LATION*	*CBD*	*DISTANCE*	*HHSIZE*	*FLOOR*
LNQTOENCAP	1.0000											
LNQTRANCAP	0.8719 ***	1.0000										
	(0.0000)											
LNQDWELCAP	0.5783 ***	0.2014 ***	1.0000									
	(0.0000)	(0.0000)										
EDU	0.4825 ***	0.4164 ***	0.3059 ***	1.0000								
	(0.0000)	(0.0000)	(0.0000)									
LNURBAN	0.0448	−0.0067	0.0943 **	0.1397 ***	1.0000							
	(0.2213)	(0.8585)	(0.0100)	(0.0001)								
LNINCCAP	0.5173 ***	0.4591 ***	0.3192 ***	0.5765 ***	0.1549 ***	1.0000						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)							
LNDENSITY	−0.0244	−0.0606	0.0961 ***	0.1877 ***	0.2015 ***	0.1825 ***	1.0000					
	(0.5048)	(0.1040)	(0.0086)	(0.0000)	(0.0000)	(0.0000)						
LNPOPULATION	0.0564	0.0160	0.0764 **	0.0959	0.9138 ***	0.1155 ***	−0.0929 **	1.0000				
	(0.1231)	(0.6686)	(0.0368)	(0.0087)	(0.0000)	(0.0016)	(0.0110)					
CBD	0.0114	0.0660 *	−0.1326 ***	−0.1995 ***	−0.2815 ***	−0.1890 ***	−0.8047 ***	−0.1438 ***	1.0000			
	(0.7563)	(0.0767)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)				
DISTANCE	0.4838 ***	0.5396 ***	0.0687 *	0.1876 ***	−0.1069 ***	0.2344 ***	−0.2845 ***	−0.0255	0.2742 ***	1.0000		
	(0.0000)	(0.0000)	(0.0608)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4865)	(0.0000)			
HHSIZE	−0.2830 ***	−0.2191 ***	−0.3474 ***	−0.2498 ***	−0.0474	−0.2764 ***	−0.1181 ***	−0.0113	0.1236 ***	−0.0200	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1954)	(0.0000)	(0.0012)	(0.7583)	(0.0007)	(0.5847)		
FLOOR	0.1899 ***	0.1090 ***	0.1861 ***	0.2175 ***	−0.0292	0.2196 ***	0.0460	0.0418	−0.0463	0.0701 *	0.1556 ***	1.0000
	(0.0000)	(0.0038)	(0.0000)	(0.0000)	(0.4316)	(0.0000)	(0.2147)	(0.2596)	(0.2123)	(0.0588)	(0.0000)	
Unit	toe/people	toe/people	toe/people		people	Int. $/month	people/km^2	people	km	people	km	m^2
Observation	748	721	746	748	748	748	748	748	748	748	748	728
Mean	−4.1252	−4.8227	−4.9389	4.4006	10.9058	5.5274	8.3175	11.0691	9.6546	4.9042	3.5227	124.7872
Std. Deviation	0.5736	0.8558	0.5274	1.3556	0.7762	0.9046	0.7623	0.5861	6.2542	4.2716	1.3732	134.1850
Minimum	−5.9395	−8.7506	−7.8953	1.0000	8.9045	3.1395	6.6777	9.2745	0.0000	0.0000	1.0000	3.0000
Maximum	−1.9025	−2.0467	−3.0373	9.0000	11.9720	8.4950	9.9354	11.7212	30.2000	37.5000	10.0000	1,000.0000

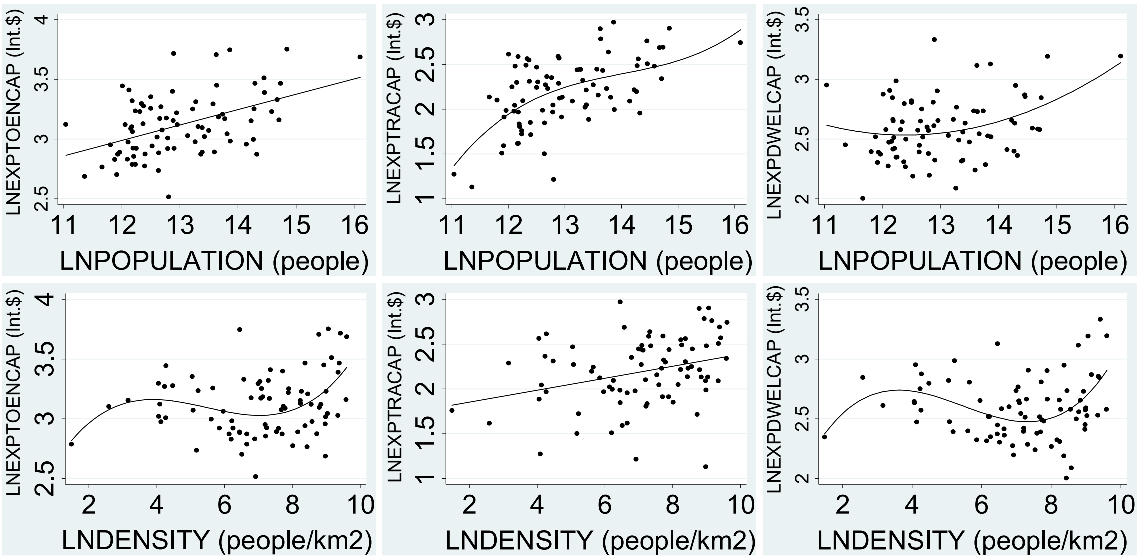
Notes: (1) LN – natural logarithm, Q – quantity, CAP – per capita, TOEN – total energy, TRAN – energy for transport, DWEL – energy for dwelling, EDU – the average of education level attained by household members, URBAN – historical urban population, INC – income, DENSITY – population density, POPULATION – city size, CBD – the distance between household's residency and the city center, DISTANCE – average commuting distance, HHSIZE – household size and FLOOR – the house size, (2) Code for education level: 1 = no schooling, 2 = not completed elementary school, 3 = elementary school, 4 = junior high school, 5 = senior high school, 6 = diploma I/II, 7 = diploma III, 8 = diploma IV/bachelor's degree, 9 = master's/doctoral degree.

For cities across Indonesia, Table 5.3 shows that, in general, the (historical) city size has a strong positive and statistically significant correlation with the per capita energy expenditure. However, the relationship between the population density and the per capita energy expenditure is ambiguous: it is statistically significant and positive for transport energy but weak for dwelling energy – implying a weak correlation between the population density and the overall per capita energy expenditure. The per capita income is positively correlated with the per capita energy expenditure, especially with the expenditure on transport energy. The same pattern holds for education, although it is somewhat weaker. Furthermore, Table 5.3 shows that, as expected, the per capita income is statistically positively correlated with the city size and population density and education is positively correlated with the per capita income.

Table 5.4 shows that, within Yogyakarta, the relationship between energy use and (historical) population size and density is rather weak and can only be confirmed for dwelling energy use. However, as for cities, our data also show that, across districts within Yogyakarta, energy correlates positively with both per capita income and education. Furthermore, as for cities across Indonesia, within Yogyakarta, the per capita income is statistically positively correlated with the city size and population density, while education correlates positively with the per capita income. In addition, the per capita income is positively correlated with the commuting distance and negatively correlated with the distance between the home and the city centre. Together with the findings for our cross-city data, this suggests that, on average, people living in larger cities, close to the city centre or in high-density areas tend to have a relatively high level of education and per capita income compared with those who live in small cities, far from the city centre or in less dense areas.

To gain further insights into the spatial dimension of energy expenditure and use, we show in Figures 5.2 and 5.3 scatter diagrams of the relationship between the per capita energy use and our spatial structure indicators for cities across Indonesia and districts in Yogyakarta Province, respectively. The figures confirm that, in general, the population size has a positive correlation with the total per capita energy expenditure and use but with substantial differences. First, it is particularly strong for transport energy use across cities and much weaker for dwelling energy use. Second, these correlations are indeed much stronger across cities than within the Yogyakarta Metropolitan Area. In addition, the figures show ambiguous results for the correlation between population density and energy use. Across cities in Indonesia, the population density correlates positively with the energy expenditure, especially with transport energy use and much less so with dwelling energy use. In contrast, across districts in Yogyakarta, the population density correlates positively with dwelling energy use, whereas the population density and transport energy show no clear correlation. Together, these patterns suggest that the compact city hypothesis does not hold for our data. In contrast, we find that, if the population size and density correlate with energy use at all, the relationship is positive – especially for transport energy use.

Figure 5.2 – Scatter Plots between Energy Expenditure and Population Density and Population across Cities in Indonesia

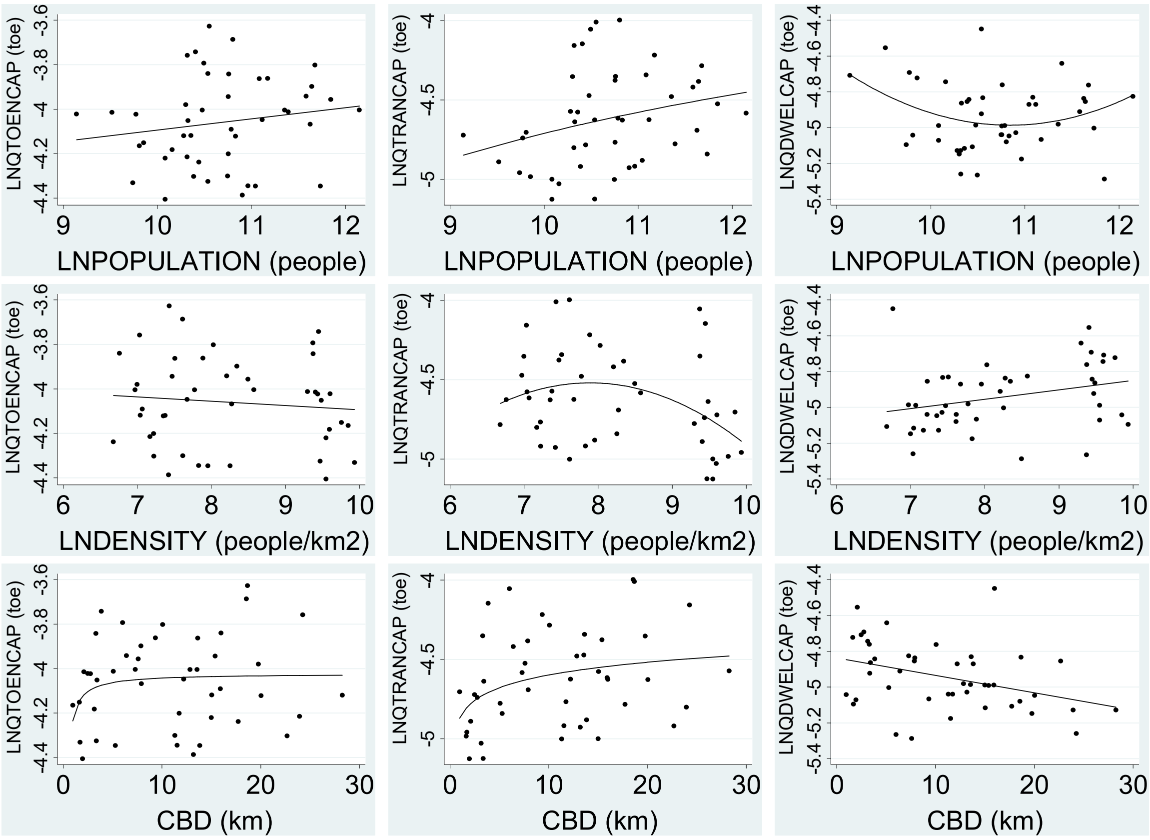


Notes: LN = natural logarithm, EXP = expenditure, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwellings, DENSITY = population density and POPULATION = city size.

In the bottom row in Figure 5.3, we also display, for districts in the Yogyakarta Metropolitan Area, the correlation coefficients between the per capita energy consumption and the distance between the home and the city centre (CBD). Clearly, the further a district is from the CBD, the lower the average energy consumption for dwellings. For transport energy use, the opposite is true, although this correlation is much weaker. In Figure 5.4, we show scatter diagrams for the Yoyakarta Metropolitan Area, including the distance to the CBD, to illustrate the role of the urban form in our analysis. In fact, Figure 5.4 shows 'bid–rent' functions, relating various variables to the distance to the CBD. According to the bid–rent model by Alonso, economic agents will choose a location that they can afford (Neuman, 2005). Based on the graphs in

Figure 5.4, we can see that people who live around the city centre or in a dense area tend to have higher levels of education and per capita income and therefore can afford to 'rent' a more expensive house.[37] People who live around the city centre also tend to have a shorter commuting distance.

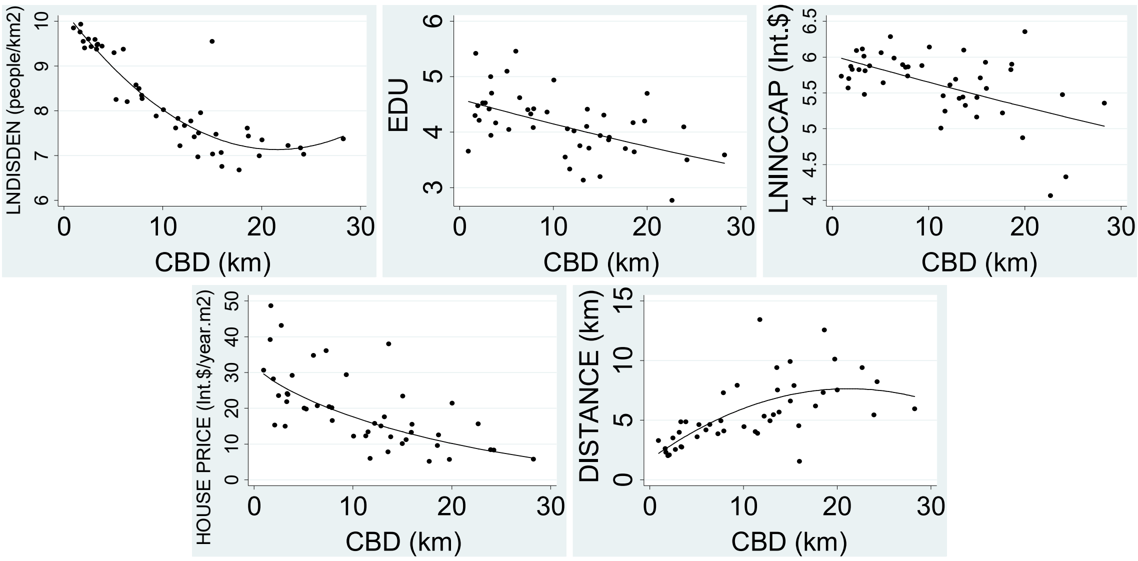
Figure 5.3 – Scatter Plots between Energy Consumption and Population Density, Distance between the Home and the City Centre and Population across Districts in Yogyakarta Province



Notes: LN = natural logarithm, EXP = expenditure, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwellings, DENSITY = population density and POPULATION = city size.

[37] In the survey, for households that do not rent but own their house, we asked how much they would ask if they were to offer their house for rent.

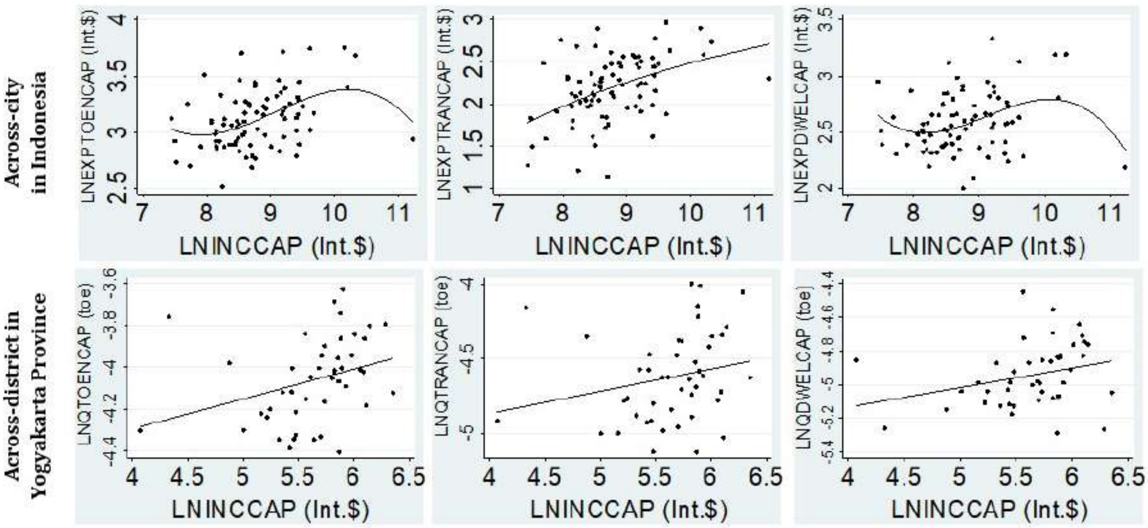
Figure 5.4 – Scatter Plots between the Distance between the Home and the City Centre and the Population Density, Education, Income, House Rental Price and Commuting Distance across Districts in Yogyakarta Province



Notes: LN = natural logarithm, CAP = per capita, CBD = distance between the home and the city centre, DISDEN = district population density, INC = income, HOUSE PRICE = house rental price per square metre, DISTANCE = average commuting distance and EDU = average education level attained by household members.

Finally, we show for both samples in Figure 5.5 that per capita income in general has a positive relationship with per capita energy use (both for transport and in total).

Figure 5.5 – Scatter Plots between Energy Use and Income



Notes: LN = natural logarithm, EXP = expenditure, Q = quantity, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwellings and INC = income.

5.4 Regression Analysis – Cities in Indonesia

We use our cross-city dataset to test the hypothesis that urbanization explains the variation in residential energy use beyond its capability to explain income. To this end, we conduct three types of analyses.

First, we investigate whether urbanization is associated with residential energy use by running the following OLS regression model:

$$\mathrm{Log}(E_i) = \alpha_1 + \beta_1 \,\mathrm{Log}(U_i) + \gamma_1 \,\mathrm{Log}(S_i) + \delta_1 \,\mathrm{Log}(C_i) + \varepsilon_{1i} \qquad (5.1)$$

where i is the city index, E is a set of per capita residential energy uses, which consist of total energy expenditure (*TOEN*), energy expenditure for transport (*TRAN*) and energy expenditure for dwellings (*DWEL*), U and S are key variables in which U is a set of urbanization indicators and S is a set of spatial variables, C is a set of control variables and ε is the error term. In the cross-city dataset for Indonesia, the energy use is measured in expenditure value, the urbanization indicators consist of education (*EDU*) and historical (2000) urban population (*URBAN*), the spatial variables contain the population density (*DENSITY*) and the city size in 2012 (*POPULATION*) and the control variables include the per capita income (*INC*) and household size (*HHSIZE*).

Second, we test the hypothesis that urbanization affects per capita income. The rationale behind this is that, on average, wages in urban areas tend to be higher than wages in rural areas. This so-called urban wage premium is caused by what Yankow (2006) described as unmeasured productive attributes or unmeasured skills and abilities of workers. In general, productivity and thus wages in urban areas are relatively high because of two effects: the most talented workers sort themselves into urban areas, and urban areas make workers more productive because of various agglomeration economies, including better matching of workers and knowledge spillovers. We test for these effects using the following OLS regression model:

$$\mathrm{Log}(Y_i) = \alpha_2 + \beta_2 \,\mathrm{Log}(U_i) + \gamma_2 \,\mathrm{Log}(S_i) + \delta_2 \,\mathrm{Log}(C_i) + \varepsilon_{2i} \qquad (5.2)$$

where the definitions of U, S, C and ε are the same as in the first model except that C does not include the per capita income, because Y represents the per capita income. In some variants of this model, we also include the per capita residential energy use as a control variable to check whether there is a causal relationship between income and energy use.

Third, we test for the hypothesis that urbanization can only explain the variation in residential energy use through income. The internal validity of testing the relationship between urbanization and energy use is under threat from a potential simultaneity bias (Antonakis et al., 2010). That is, urbanization may affect energy use through income, but (improved) access to modern energy sources may affect the per capita income and clustering of firms and people in urban areas, given the positive impact of urban energy transitions in low- and middle-income countries on local economic productivity (Barnes et al., 2005). Therefore, we develop a 2SLS regression model, which is an instrumental variable regression model that first predicts the logarithm of income per capita $\bar{Y}$, according to equation (5.2), in which the set of urbanization indicators U is replaced with the instrumental variable(s). Instrumental variables should have a high correlation with the urban population in 2012 for our cross-city dataset while having no correlation with the error in equation (5.3). We use the lagged city population and the completion of tertiary education as instruments for urbanization, following the intuition that, in a country like Indonesia, tertiary education is a typical large-city phenomenon (Kotter, 2004; Zu-chao & Wen, 2006; Edmonds, 2013; United Nations, 2015), while it is not directly related to energy use. In the second stage, we regress the logarithm of per capita residential energy use on the instrumented variable $\bar{Y}$, that is, the value of per capita income predicted in the first stage, according to:

$$\log(E_i) = \alpha_3 + \gamma_3 \log(S_i) + \delta_3 \log(C_i) + \lambda \log(\hat{Y}) + \varepsilon_{3i} \quad (5.3)$$

where E, S and ε are defined as in equation (5.1), C is defined as in equation (5.2) and $\hat{Y}$ is, as noted, the predicted value of the first stage of the 2SLS regression model, which is represented by equation (5.2). If the instrumented variable $\bar{Y}$ can indeed explain the variation in energy use, then we can confirm that the city size and urban form influence residential energy use indirectly through the impact that they have on the per capita income. Otherwise, we may conclude that the city size and urban form affect energy use directly, beyond or instead of the effect that they have on the per capita income.

Before testing this third hypothesis, several tests should be performed to make sure that our instruments are valid and to guarantee that the structural equations in the 2SLS regression model are specified correctly. The first test is the endogeneity test. The null hypothesis of this test is that the instrumented variable, namely per capita income, can be treated as exogenous, which simply confirms that the instrumented variable is not endogenously defined by the instrumental variables. The second test is the over-identifying restrictions test with the null hypothesis that the instrumental variables are valid. The test basically consists of two simultaneous tests, specifically a test to check whether the instrumental variables have no relationship with the error term and a test to determine whether the structural equations in the 2SLS regression model are mis-specified or whether one or more of the instrumental variables should have a direct relationship with the dependent variable. The third test is the first-stage test, which has as its null hypothesis that the instrumental variables are weak.

If the first test shows that the instrumented variable is exogenous, we may conclude that urbanization has a direct effect on per capita energy expenditure. If the second and the third hypothesis are accepted, we may conclude that urbanization only has an indirect effect on residential energy use through its impact on income. This would mean that the change from a rural lifestyle to an urban lifestyle has no direct effect on energy use other than through the change in income.

Does Urbanization Explain Energy Use?

Table 5.5 displays the results of our OLS regression model with per capita energy expenditure as the dependent variable (equation 5.1). The results show that various indicators related to urbanization positively affect energy expenditure. First, we find that in general education (EDU), the historical urban population (LNURBAN), the city size (LNPOPULATION) and the population density (LNDENSITY) all have a statistically significant positive effect on per capita energy expenditure. Second, we find, as expected, that in general per capita energy expenditure is influenced positively by per capita income and negatively by household size.

A closer look at the regression results also shows that, when we include in our regression model a combination of urbanization indicators and control variables, the impact of the historical urban population (LNURBAN) and population density on energy expenditure is not always robust. Especially the role of the population density is not straightforward: in the more complete model specifications, its coefficient becomes statistically significantly negative except for transport energy expenditure. The coefficient for the historical urban population tends to become statistically insignificant in the more complete specifications. Note that we did not enter the city size into Model 8 due to its high correlation with the historical urban population. The impact of the city size appears to be significantly positive for all types of energy expenditure. Finally, the effect of the per capita income on the per capita energy expenditure for dwellings is statistically insignificant.

In sum, the regression results in Table 5.5 show evidence that both per capita income and urbanization influence per capita energy use. The impact of per capita income is positive, and the impact of urbanization is not straightforward. In our multivariate analyses, we see that the urbanization indicators become largely insignificant in explaining transport energy expenditure, while dwelling energy expenditure appears to be lower in cities with a higher population density.

Does Urbanization Explain Income?

Table 5.6 displays the OLS regression models with the per capita income as the dependent variable (equation 5.2). Besides including urban, spatial and control variables, we include energy variables in our regression model. From Table 5.6, we can conclude that education and the historical urban population have a significantly positive effect on the per capita income. However, including per capita energy expenditure in the model makes the effect of education statistically insignificant. As regards the urbanization indicators, we find that the city size and population density have a significantly positive effect on the per capita income. However, including the historical urban population in the model changes the effect of the population density due to the moderate correlation between them. The effect of the household size on the income is positive but statistically insignificant. Finally, we find that the total per capita energy expenditure and per capita energy expenditure for transport have a significantly positive effect on the per capita income. Hence, our results indeed suggest that a possible threat exists from causality between per capita income and per capita energy expenditure.

Does Urbanization Explain Energy Use through Income?

Table 5.7 displays the second stage of our 2SLS regression model with per capita energy use as the dependent variable and education and the historical urban population as the instrumental variables for urbanization (equation 5.3). As noted in section 5.3, this approach first requires the testing of the validity of our instrumental variables. The results in Table 5.7 show that the instrumented variable, that is, per capita income, is endogenous and that the various instrumental variables are not weak. The χ^2 and *F*-values for the endogeneity test are statistically significant for all the models except for Model 2F and Model 2G. The instrumental variables are strong in all the models based on the *F*-value for the first-stage test. The overidentifying restrictions show that the instrumental variables are also valid at the significance level of 10%, except for Models 4E, 2G and 4G. However, in Model 2G, the instrumental variables are valid at the significance level of 5%.

Furthermore, the results in Table 5.7 show that the per capita income has a significantly positive impact on the per capita energy expenditure. Model 6D in Table 5.6 shows the first-stage regression results of Model 4E, Model 4F and Model 4G in Table 5.7.[38] The regression results for Model 6D in Table 5.6 show that education and the historical urban population have a positive effect on the per capita income and that the effect of the historical urban population is statistically significant. Because the effect of the per capita income in the 2SLS regression models is statistically significant, and given that the overidentifying restrictions test indicates that the instrumental variables are valid or that the structural equation models are not mis-specified, we can conclude that urbanization has a significantly positive effect on the per capita energy expenditure through the per capita income or that urbanization should not have a direct relationship with the per capita energy expenditure. According to Model 6D, the per capita income will increase by 7.71% when the mean of our education variable (years of schooling of the population aged 15 years or more) increases by one year, while the per capita income will increase by 0.34% when the historical urban population level increases by 1%. In addition, the results for Model 4E, Model 4F and Model 4G imply that a 1% increase in the per capita income will increase the per capita total energy expenditure by 0.38%, the per capita energy expenditure on transport by 0.45% and the per capita energy expenditure on dwellings by 0.35%.

[38] The first-stage regression models of the other models in Table 5.7 are not presented in this chapter.

We also find that the city size has a positive effect on the per capita energy expenditure. The effect is statistically significant for the per capita total energy expenditure and per capita transport energy expenditure. More precisely, our results imply that an increase of 1% in the city size will increase the per capita total energy expenditure and per capita energy expenditure on transport by 0.08% and 0.13%, respectively (see Models 2E and 2F). In contrast, we find that the population density has a negative but statistically insignificant impact on the per capita energy expenditure. Note that, in Model 4E, Model 4F and Model 4G, when we include the city size along with the population density, the statistically significant effects of the population size in Model 4E and Model 4F become statistically insignificant. Finally, we find that the household size has a statistically significant negative impact on the per capita energy expenditure. An increase in the household size by 1 member will increase the per capita energy expenditure by around 24%–26%.

In sum, the main conclusion of our 2SLS regression models is that urbanization affects the per capita energy expenditure indirectly through the per capita income. The effect of urbanization on the per capita energy expenditure is positive. Thus, the higher the urbanization rate, the larger the per capita energy expenditure.

Table 5.5 – OLS Regression Explaining the Energy Expenditure, Cross-City Analysis for Indonesia

Independent Variables	Dependent Variable: *LNEXPTOENCAP*								
	Model 1A	Model 2A	Model 3A	Model 4A	Model 5A	Model 6A	Model 7A	Model 8A	Model 9A
Key Variables									
EDU	0.0380**					0.0470***		0.0413***	0.0545***
	(0.0155)					(0.0143)		(0.0148)	(0.0148)
LNURBAN		0.1033***				0.0558**		0.0411*	0.0824***
		(0.0236)				(0.0211)		(0.0217)	(0.0272)
LNPOPULATION			0.1291***				0.0929***		
			(0.0258)				(0.0260)		
LNDENSITY				0.0289*			0.0097		−0.0402**
				(0.0152)			(0.0133)		(0.0185)
Control Variable									
LNINCCAP					0.1484***			0.0785**	0.0664*
					(0.0541)			(0.0374)	(0.0338)
HHSIZE						−0.2631***	−0.2136***	−0.2660***	−0.2605***
						(0.0547)	(0.0462)	(0.0499)	(0.0512)
Constant	2.7688***	1.8522***	1.4391***	2.9138***	1.8157***	3.0684***	2.7042***	2.6213***	2.3557***
	(0.1338)	(0.2974)	(0.3351)	(0.1037)	(0.4692)	(0.3337)	(0.3610)	(0.3584)	(0.3425)
$R^2_{adjusted}$	0.0457	0.1984	0.2142	0.0273	0.1312	0.4838	0.3995	0.5090	0.5387
F	5.9799**	19.1214***	25.0392***	3.6340**	7.5357***	15.1032***	14.5930***	15.4875***	16.6191***
N	82	71	82	82	82	71	82	71	71

Independent Variables	Dependent Variable: *LNEXPTRANCAP*								
	Model 1B	Model 2B	Model 3B	Model 4B	Model 5B	Model 6B	Model 7B	Model 8B	Model 9B
Key Variables									
EDU	0.0389					0.0284		0.0199	0.0321
	(0.0239)					(0.0228)		(0.0231)	(0.0265)
LNURBAN		0.1709***				0.1344***		0.1121***	0.1504
		(0.0292)				(0.0296)		(0.0339)	(0.0478)
LNPOPULATION			0.2243***				0.1787***		
			(0.0367)				(0.0447)		
LNDENSITY				0.0669***			0.0295		−0.0373
				(0.0227)			(0.0220)		(0.0326)
Control Variable									
LNINCCAP					0.2564***			0.1189**	0.1077**
					(0.0653)			(0.0494)	(0.0502)
HHSIZE						−0.2447***	−0.1750**	−0.2491***	−0.2440***
						(0.0669)	(0.0719)	(0.0621)	(0.0631)
Constant	1.8346***	0.0982	−0.7257	1.7190***	−0.0589	1.2741***	0.3656	0.5969	0.3504
	(0.2166)	(0.3781)	(0.4887)	(0.1656)	(0.5783)	(0.4618)	(0.6978)	(0.4439)	(0.4952)
$R^2_{adjusted}$	0.0151	0.2732	0.2978	0.0843	0.1821	0.3775	0.3523	0.4055	0.4122
F	2.6570	34.2903**	37.3553***	8.7141***	15.4373***	17.2840***	18.8679***	15.2405***	11.9635***
N	82	71	82	82	82	71	82	71	71

Notes: (1) EXP = expenditure, CAP – per capita and LN = natural logarithm. (2) *, ** and *** = significant at 10%, 5% and 1%, respectively. (3) robust standard errors are presented in the parenthesis.

Table 5.5 – OLS Regression Explaining the Energy Expenditure, Cross-City Analysis for Indonesia (continued)

Independent Variables	Dependent Variable: *LNEXPDWELCAP*								
	Model 1C	**Model 2C**	**Model 3C**	**Model 4C**	**Model 5C**	**Model 6C**	**Model 7C**	**Model 8C**	**Model 9C**
Key Variables									
EDU	0.0370 **					0.0583 ***		0.0552 ***	0.0708 ***
	(0.0166)					(0.0161)		(0.0169)	(0.0158)
LNURBAN		0.0653 **				0.0101		0.0020	0.0508
		(0.0288)				(0.0287)		(0.0276)	(0.0344)
LNPOPULATION			0.0799 **				0.0505 ***		
			(0.0324)				(0.0324)		
LNDENSITY				0.0072			−0.0031		−0.0474 **
				(0.0167)			(0.0144)		(0.0198)
Control Variable									
LNINCCAP					0.0828			0.0431	0.0289
					(0.0606)			(0.0431)	(0.0391)
HHSIZE						−0.2843 ***	−0.2333 ***	−0.2859 ***	−0.2794 ***
						(0.0728)	(0.0578)	(0.0706)	(0.0712)
Constant	2.2494 ***	1.7906 ***	1.5502 ***	2.5393 ***	1.8631 **	3.0828 ***	2.8969 ***	2.8371 ***	2.5236 ***
	(0.1419)	(0.3598)	(0.4222)	(0.1132)	(0.5233)	(0.04424)	(0.4719)	(0.5596)	(0.5355)
$R^2_{adjusted}$	0.0424	0.0686	0.0739	−0.0101	0.0320	0.4087	0.2992	0.4094	0.4512
F	4.9718 **	5.1272	6.0747 **	0.1825	1.8637 *	7.9270 ***	6.9923 ***	7.0952 ***	7.8020 ***
N	82	71	82	82	82	71	82	71	71

Notes: (1) EXP = expenditure, CAP = per capita and LN = natural logarithm. (2) *, ** and *** = significant at 10%, 5% and 1%, respectively. (3) robust standard errors are presented in the parenthesis.

Table 5.6 – OLS Regression Explaining Income across Cities in Indonesia

Independent Variable	Dependent Variable: *LNINCCAP*										
	Model 1D	Model 2D	Model 3D	Model 4D	Model 5D	Model 6D	Model 7D	Model 8D	Model 9D	Model 10D	Model 11D
Key Variables											
EDU	0.1178 ***				0.0719 *	0.0771				0.0032	0.0248
	(0.0337)				(0.0374)	(0.0571)				(0.0577)	(0.0520)
LNURBAN		0.2203 ***			0.1875 ***	0.3447 **				0.3690 **	0.3276 **
		(0.0578)			(0.0629)	(0.1544)				(0.1567)	(0.1519)
LNPOPULATION			0.2214 ***			−0.1008				−0.2266	−0.1892
			(0.0783)			(0.1744)				(0.1877)	(0.1791)
LNDENSITY				0.1003 ***		−0.0827 **				−0.0600	−0.0615
				(0.0370)		(0.0377)				(0.0402)	(0.0405)
LNEXPTOENCAP							0.9567 ***			0.8867 **	
							(0.2665)			(0.3387)	
LNEXPTRANCAP								0.7495 ***			0.4558 *
								(0.1823)			(0.2551)
LNEXPDWELCAP									0.5308		0.2582
									(0.3394)		(0.3179)
Control Variable											
HHSIZE					0.0368	0.0483				0.2801 *	0.2315
					(0.1510)	(0.1534)				(0.1654)	(0.1586)
Constant	7.6939 ***	6.0955 ***	5.8981 ***	8.0684 ***	5.6959 ***	5.5536 ***	5.7944 ***	7.1345 ***	7.4028 ***	3.7024 **	4.8317 ***
	(0.3056)	(0.7199)	(1.0142)	(0.2588)	(0.9765)	(1.2115)	(0.8345)	(0.3947)	(0.8900)	(1.4667)	(1.4881)
$R^2_{adjusted}$	0.0743	0.1411	0.0909	0.0619	0.1533	0.1492	0.1312	0.1821	0.0320	0.1920	0.1756
F	12.2104 ***	14.5455 **	7.9998 ***	7.3479 **	6.4511 ***	4.9937 ***	12.8848 ***	16.9009 ***	2.4466 **	4.98895 ***	3.8671 ***
N	82	71	82	82	71	71	82	82	82	71	71

Notes: (1) EXP = expenditure, CAP = per capita and LN = natural logarithm. (2) *, ** and *** = significant at 10%, 5% and 1%, respectively. (3) robust standard errors are presented in the parenthesis.

Table 5.7 – 2SLS Regression Explaining Energy Expenditure, Cross-City Analysis for Indonesia

Independent Variable	Dependent Variable: *LNEXPTOENCAP*				Dependent Variable: *LNEXPTRANCAP*				Dependent Variable: *LNEXPDWELCAP*			
	Model 1E	Model 2E	Model 3E	Model 4E	Model 1F	Model 2F	Model 3F	Model 4F	Model 1G	Model 2G	Model 3G	Model 4G
Endogenous												
Chi²	8.1453 ***	2.8984 *	9.4202 ***	8.0487 ***	7.8553 ***	2.0722	6.3998 **	4.0250 **	5.0861 **	1.9012	7.5275 ***	7.0774 ***
	(0.0043)	(0.0887)	(0.0021)	(0.0046)	(0.0051)	(0.1500)	(0.0114)	(0.0448)	(0.0241)	(0.1679)	(0.0061)	(0.0078)
F	10.4180 ***	3.1240 *	15.3181 ***	9.6549 ***	12.4924 ***	2.5530	8.5147 ***	4.4139 **	5.1371 **	1.7144	10.8711***	7.5636 ***
	(0.0019)	(0.0817)	(0.0002)	(0.0028)	(0.0007)	(0.1148)	(0.0048)	(0.0395)	(0.0266)	(0.1949)	(0.0016)	(0.0077)
Overidentifying Restrictions												
Chi²	0.4567	2.2861	0.4273	7.0299 ***	2.1916	0.0001	2.1021	0.5962	0.0601	3.6589 *	0.0267	7.9817 ***
	(0.4991)	(0.1305)	(0.5133)	(0.0080)	(0.1388)	(0.9917)	(0.1471)	(0.4400)	(0.8064)	(0.0558)	(0.8701)	(0.0047)
First Stage												
$R^2_{adjusted}$	0.1649	0.1524	0.1695	0.1492	0.1649	0.1524	0.1695	0.1492	0.1649	0.1524	0.1695	0.1492
F	9.8963 ***	6.5417 ***	9.7136 ***	9.7083 ***	9.8963 ***	6.5417 ***	9.7136 ***	9.7083 ***	9.8963 ***	6.5417 ***	9.7136 ***	9.7083 ***
	(0.0002)	(0.0025)	(0.0002)	(0.0002)	(0.0002)	(0.0025)	(0.0002)	(0.0002)	(0.0002)	(0.0025)	(0.0002)	(0.0002)
Instrumented												
LNINCCAP	0.4287 ***	0.2737 **	0.5048 ***	0.3754 ***	0.6367 ***	0.3808 **	0.6520 ***	0.4521 ***	0.3110 ***	0.2080 *	0.4392 ***	0.3481 ***
	(0.1032)	(0.1070)	(0.1260)	(0.0987)	(0.1666)	(0.1677)	(0.1972)	(0.1596)	(0.1023)	(0.1192)	(0.1343)	(0.1086)
Key Variables												
LNPOPULATION		0.0793 **		0.0315		0.1319 **		0.0818		0.0521		0.0027
		(0.0381)		(0.0407)		(0.0612)		(0.0622)		(0.0386)		(0.0394)
LNDENSITY			−0.0152	−0.0109			−0.0021	−0.0009			−0.0262	−0.0200
			(0.0234)	(0.0172)			(0.0323)	(0.0252)			(0.0244)	(0.2870)
Control Variable												
HHSIZE				−0.2452 ***				−0.2491 ***				−0.2533 ***
				(0.0481)				(0.0664)				(0.0609)
Constant	−0.6502	−0.3198	−1.2146	0.4690	−3.4004 **	−2.8683 **	−3.5201**	−1.8363	−0.1456	0.0815	−1.0931	0.6487
	(0.9086)	(0.7589)	(1.0404)	(0.6782)	(1.4767)	(1.2231)	(1.6392)	(1.2085)	(0.8998)	(0.8415)	(1.0993)	(0.7939)
$R^2_{adjusted}$	.	0.0574	.	0.0347	.	0.1318	.	0.1305	.	.	.	.
Chi²	17.2486 ***	26.6656 ***	19.3996 ***	51.9047 ***	14.5983 ***	22.7649 ***	15.6528 ***	33.4416 ***	9.2374 ***	12.2869 ***	11.9782 ***	27.8376 ***
N	71	71	71	71	71	71	71	71	71	71	71	71

Notes: (1) EXP = expenditure, CAP = per capita and LN = natural logarithm. (2) *, ** and *** = significant at 10%, 5% and 1%, respectively, (3) robust standard errors are presented in the parenthesis, but for endogenous, overidentifying restrictions and first stage, values in the parenthesis are p-value. (4) Instrument variables = EDU and LNURBAN

5.5 Regression Analysis – Districts in Yogyakarta

In this section, we present the results of our survey across districts in the Yogyakarta Metropolitan Area. As noted, through the survey, we collected information about energy consumption and travel behaviour from 748 urban households within Yogyakarta Province. In our regression analysis, we take advantage of the individual dimension of these survey data, which allows us to evaluate the extent to which the observed impact of urban indicators on energy consumption is influenced by the spatial sorting of people across districts in Yogyakarta Province. Clearly, urban residents are not homogeneous, and individual differences in income and energy use patterns may affect their preferences for living in different parts of the metropolitan area. Ignoring these and other sorting effects may lead to inaccurate estimates of the impact of urban indicators on energy use.

As noted in the introduction to this chapter, we therefore adopt an estimation strategy that Combes et al. (2008) developed to control for worker heterogeneity in explaining spatial wage disparities across local labour markets in France and that has subsequently been applied in many other papers (e.g., Groot et al., 2014; Verstraten et al., 2019). We modify this approach by applying it to energy consumption patterns across the urban districts in Yogyakarta Province. More specifically, in a two-step procedure, we first control for sorting by explaining the spatial disparity in energy consumption from observed characteristics of individual households and a local district effect that represents the unobserved local characteristics of the urban area where people live. Subsequently, we identify the role of local urban characteristics like population size, population density and distance to the city centre in explaining these local urban area effects.

Thus, in the first stage of our analysis, we explain household energy use from household characteristics and a dummy variable for the urban district as follows:

$$\log(E_j) = a_1 + b_1 H_j + \Sigma c_{1k} D_k + e_{1j} \tag{5.4}$$

where j is a household index, k is a district index, E is a set of per capita residential energy use measures that consists of the total energy consumption ($TOEN$), energy consumption for transport ($TRAN$) and energy consumption for dwellings ($DWEL$) and H is a set of household characteristics that consists of education (EDU), the log of per capita income (*LNINCCAP*), the household size (*HHSIZE*), the house size (*FLOOR*) and the commuting distance (*DISTANCE*); a_1 is the constant and D_k is a dummy variable for district k.

In the second stage of the analysis, we explain the urban area effects (c_{1k}) obtained from equation (5.4) from area characteristics as follows:

$$c_{1k} = a_2 + b_2 A_j + e_{2j} \tag{5.5}$$

where c_{1k} is the urban area fixed effect of area k estimated in the first stage and A are the urban area characteristics that consist of the log of the population in 2015 (*LNPOPULATION*), historical (2000) urban population (*LNURBAN*), population density (*LNDENSITY*) the distance between the urban area and the city centre (*CBD*).

Table 5.8 presents the first-stage OLS regression results with the per capita energy consumption as the dependent variable and household characteristics as well as the urban area fixed effects as the independent variables. The results show that household characteristics in combination with urban area fixed effects can explain about 40% of the per capita total energy consumption and per capita energy consumption for transport, whereas they can only explain about 20% of the per capita dwelling energy consumption.

Table 5.8 – OLS Regression Explaining Energy Consumption, Cross-Household Analysis for Yogyakarta Province

Independent Variable	Dependent Variable		
	LNQTOENCAP	*LNQTRANCAP*	*LNQDWELCAP*
EDU	0.0975***	0.1221***	0.0537***
	(0.0177)	(0.0294)	(0.0172)
LNINCCAP	0.1484***	0.2121***	0.0663***
	(0.0233)	(0.0383)	(0.0244)
HHSIZE	–0.0724***	–0.0526**	–0.1138***
	(0.0140)	(0.0218)	(0.0150)
FLOOR	0.0004**	0.0001	0.0008***
	(0.0002)	(0.0002)	(0.0002)
DIST	0.0499**	0.0871***	0.0012
	(0.0052)	(0.0095)	(0.0044)
Constant	–3.5714***	–4.5357***	–4.3362***
	(0.0747)	(0.0667)	(0.0416)
District Dummies	Yes	Yes	Yes
$R^2_{adjusted}$	0.4647	0.4197	0.2260
F	13.6173***	.	9.7592***
N	728	702	727

Notes: (1) Q = quantity, CAP = per capita and LN = natural logarithm. (2) *, ** and *** = significant at the 10%, 5% and 1% level, respectively. (3) Robust standard errors are presented in the parentheses. (4) The regression coefficients for 44 district dummies are not presented.

The results in Table 5.8 show that education and the per capita income also have a statistically significant positive effect on the per capita energy consumption at the individual level. The values for the coefficients imply that an increase of 1% in the per capita income increases the per capita total energy consumption by 0.15%, the per capita energy consumption for transport by 0.21% and the per capita energy consumption for dwellings by 0.07%. Furthermore, Table 5.8 shows that the household size has a statistically significant negative effect on the per capita energy consumption, with the largest effect on the per capita energy consumption for dwellings. An increase in the household size by 1 person implies a reduction in the per capita dwelling energy consumption by 11.4% and in the per capita energy consumption for transport by 5.3%. The latter may be caused by household members sharing motor vehicles. We also find that a bigger house size significantly increases the per capita total energy consumption and the per capita energy consumption for dwellings. Finally, the results show that a longer commuting distance has a statistically significant positive effect on the per capita total energy consumption and per capita energy consumption for transport.

Table 5.9 – OLS Regression Explaining Energy Consumption Residuals across Households in Yogyakarta Province

Independent Variable	Dependent Variable: *RESLNQTOENCAP*						
	Model 1H	Model 2H	Model 3H	Model 4H	Model 5H	Model 6H	Model 7H
LNPOPULATION	–0.0093			–0.0101	–0.0113		0.0064
	(0.0304)			(0.0304)	(0.0300)		(0.0304)
LNDENSITY		0.0011		–0.0014		0.0349	0.0388
		(0.0265)		(0.0276)		(0.0376)	(0.0387)
CBD			0.0017		0.0018	0.0057	0.0061
			(0.0039)		(0.0039)	(0.0057)	(0.0061)
Constant	–0.4497	–0.5582**	–0.5672***	0.4289	–0.4469	–0.8973**	–1.0015
	(0.3372)	(0.2209)	(0.0438)	(0.4530)	(0.3382)	(0.3499)	(0.5648)
$R^2_{adjusted}$	–0.0221	–0.0238	–0.0173	–0.0470	–0.0395	–0.0240	–0.0490
F	0.0933	0.0017***	0.1812	0.0560**	0.1921	0.5417	0.3880***
N	44	44	44	44	44	44	44

Notes: (1) RESX = residuals of a model with X as the dependent variable. (2) *, ** and *** = significant at the 10%, 5% and 1% level, respectively. (3) Robust standard errors are presented in parentheses. (4) CBD is the distance from a district to the CBD (central business district).

Table 5.9 – OLS Regression Explaining Energy Consumption Residuals, Cross-Household Analysis for Yogyakarta Province (continued)

Independent Variable	Dependent Variable: RESLNQTRANCAP						
	Model 1I	**Model 2I**	**Model 3I**	**Model 4I**	**Model 5I**	**Model 6I**	**Model 7I**
LNPOPULATION	–0.0205			–0.0324	–0.0258		–0.0040
	(0.0375)			(0.0380)	(0.0350)		(0.0432)
LNDENSITY		–0.0128		–0.0208		0.0504	0.0479
		(0.0326)		(0.0346)		(0.0485)	(0.0591)
CBD			0.0049		0.0051	0.0107	0.0105
			(0.0044)		(0.0044)	(0.0067)	(0.0077)
Constant	–0.0168	–0.1302	–0.2878***	0.2813	–0.0140	–0.7642*	–0.6992
	(0.4147)	(0.2698)	(0.0536)	(0.5783)	(0.3956)	(0.4501)	(0.9073)
$R^2_{adjusted}$	–0.0188	–0.0191	0.0101	–0.0328	–0.0059	0. 0091	–0.0156
F	0.2979	0.1554	1.1902	0.4240	1.0133	1.2938	0.8737
N	44	44	44	44	44	44	44

Notes: (1) RESX = residuals of a model with X as the dependent variable. (2) *, ** and *** = significant at the 10%, 5% and 1% level, respectively. (3) Robust standard errors are presented in parentheses. (4) CBD is the distance from a district to the CBD (central business district).

Table 5.9 – OLS Regression Explaining Energy Consumption Residuals, Cross-Household Analysis for Yogyakarta Province (continued)

Independent Variable	Dependent Variable: *RESLNQDWELCAP*						
	Model 1J	**Model 2J**	**Model 3J**	**Model 4J**	**Model 5J**	**Model 6J**	**Model 7J**
LNPOPULATION	–0.0006			–0.0013	–0.0016		–0.0138
	(0.0368)			(0.0354)	(0.0359)		(0.0405)
LNDENSITY		–0.0030		–0.0033		–0.0252	–0.0337
		(0.0316)		(0.0322)		(0.0506)	(0.0583)
CBD			–0.0008		–0.0009	–0.0038	–0.0046
			(0.0037)		(0.0036)	(0.0055)	(0.0062)
Constant	–0.6427	–0.6120**	–0.6273***	–0.0595	–0.6440	–0.3887	–0.1626
	(0.4045)	(0.2449)	(0.0562)	(0.4896)	(0.4040)	(0.4473)	(0.8251)
$R^2_{adjusted}$	–0.0238	–0.0235	–0.0227	–0.0485	–0.0476	–0.0412	–0.0654
F	0.0003	0.0088	0.0528	0.0055	0.0318	0.2383	0.1909
N	44	44	44	44	44	44	44

Notes: (1) RESX = residuals of a model with X as the dependent variable. (2) *, ** and *** = significant at the 10%, 5% and 1% level, respectively. (3) Robust standard errors are presented in parentheses. (4) CBD is the distance from a district to the CBD (central business district).

In Table 5.9, we present the second-stage OLS regression results with the urban area effects (c_{1j}) obtained from equation (5.4) as the dependent variable. The independent variables are the urban area characteristics. The results show first that all urban area characteristics have no significant effects on the 'residuals' of the per capita energy consumption.[39] Despite the insignificant effects, the sign effects of the population size are all negative except in Model 7H. The sign effects of the population density on the residuals of per capita energy consumption for transport are also negative but only when we do not include the distance to the city centre in the model (see Models 2I and 4I). On the other hand, in Models 3I and 5I, the sign effects of the distance to the

[39] Note that the term 'residuals' are different from the error models (e_{1j}) in equation (5.4); instead they refer to the urban area effects (c_{1k}) obtained from equation (5.4).

city centre on the residuals of the per capita energy consumption for transport are positive, which might be because the population density and the distance to the city centre have a negative correlation (see Table 5.4 and Figure 5.4).[40]

Together, these results imply that, in the Yogyakarta Metropolitan Area, the urban form has a distinct effect on the energy consumption, with the distance to the city centre being a crucial determinant. Clearly, the impact of this distance on transport energy use is the transmission channel through which it affects the total energy consumption. Figure 5.4 and Table 5.4 show that the commuting distance indeed has a positive correlation with the distance to the city centre (and a negative correlation with the population density). Hence, people who live closer to the city centre (in a denser district) tend to consume less energy, because their relatively short commuting distance saves energy required for transport.

Further, the negative sign effects of the population density on the residuals of per capita energy consumption for dwellings are negative. However, there is no support from Figure 5.3 and Table 5.4 for the idea that the population density has a negative correlation with the per capita energy consumption for dwellings.

The sign effects of the distance to the city centre on the residuals of the per capita energy consumption for dwellings are also negative. Figure 5.3 and Table 5.4 show a negative significant correlation between the distance to the city centre and the per capita energy consumption for dwellings. The negative effects might be because, around the city centre, buildings are more crowded, while, in areas farther from the city centre, buildings are less dense. Therefore, in areas around the city centre, the air should feel warmer, and this could encourage houses around the city centre to have an air conditioner, which will need more electricity.

[40] Note that (potential) multicollinearity between population density and the distance to the CBD, as indicated by Figure 5.4 and the high correlation coefficient in Table 5.4, may cause the sign of one or both variables to change if both variables are included in the same regression model. Given the strong negative correlation between the two variables, their regression coefficients are expected to have different signs in case of a serious multicollinearity problem. However, the results show that when both variables are included in the same model, the negative effect of population density in model 4H and 4I changes into a positive effect (see model 6H, 7H, 6I and 7I).

5.6 Discussion and Conclusion

This chapter analysed how the city size and urban form affect the residential energy use in Indonesian cities. Traditionally, energy consumption and emission levels are highest in rich countries, but nowadays both urban and GHG emission growth are largely driven by countries in the global South. Despite the importance of urban areas for energy use and global emissions, data on urban energy use are in short supply, especially when it comes to urban areas in the global South. As a consequence, most of the existing literature on the interaction between energy use and urbanization has focused on countries in the Western world, while the available research on energy use in developing countries has largely ignored the impact of the spatial structure on economic development.

The research presented in this chapter contributes to filling this research gap. For our analyses, we made use of two datasets. Our first dataset comprised 71 cities across Indonesia and included data series at the city level. These data were collected from the Indonesian National Statistics Office. Our second dataset included household-level information across 45 districts within the metropolitan area of Yogyakarta. These data were collected through a survey of 748 households, which we conducted ourselves in 2016. Using the first dataset and a two-stage regression model, we first investigated whether urbanization influences per capita energy consumption per se, that is, beyond the ability of urbanization to explain increasing energy use through its influence on per capita incomes. Using the second dataset and the two-stage regression approach developed by Combes et al. (2008), we examined the extent to which the observed impact of urban indicators on energy consumption is influenced by the spatial sorting of people within a large metropolitan area.

The reason for using two-stage regression strategies was their ability to prevent potential biases in our estimates that may arise from reverse causality and sorting. That is, urbanization may influence energy use through income, but (improved) access to modern energy sources may also affect the per capita income and the clustering of firms and people in urban areas, given the positive impact of urban energy transitions in low- and middle-income countries on local economic productivity. In addition, differences in income and energy use patterns across households may affect their preferences for living in different parts of the metropolitan area. Ignoring the potential role of these effects may result in inaccurate estimates of the impact of urban indicators on energy use.

In short, we found no evidence that larger and denser cities have a direct effect on energy use other than through an income effect. The income effect is substantial: a 1% increase in the per capita income increases the per capita total energy expenditure by 0.38%, per capita energy expenditure on transport by 0.45% and per capita energy expenditure on dwellings by 0.35%. We also found that the city size has a significant positive effect on the per capita energy expenditure. More precisely, our results indicated that a 1% increase in the city size will increase the per capita total energy expenditure and per capita energy expenditure on transport by 0.08% and 0.13%, respectively. In contrast, across cities, we found no statistically significant impact of population density on energy expenditure. Within the metropolitan area of Yogyakarta, we found that household characteristics explain only about 40% of the per capita total energy consumption and per capita energy consumption for transport, whereas they explain only about 20% of the per capita dwelling energy consumption. Hence, urban characteristics play an important role in explaining energy use. Our regression results showed that the distance to the city centre – which is correlated with the population density – plays a crucial role in explaining the within-city variation in energy consumption. People who live closer to the city centre (in a denser district) tend to consume less energy, because their relatively short commuting distance saves energy consumption for transport. We also found an indication that people who live far from the city centre might consume less energy, that is, electricity, in their dwelling.

The positive effect of the per capita income on energy use reinforces the results from previous studies (Ewing & Rong, 2008; Permana et al., 2008; Glaeser & Kahn, 2010; Poumanyvong et al., 2012; Astinawaty & Kustiwan, 2013; Wijaya, 2013; Andadari et al., 2014). Using cross-city data, we found no support for the compact city hypothesis (Glaeser & Kahn, 2010), but we did find support for this hypothesis within the metropolitan area of Yogyakarta. In general, the effect sizes that we found clearly show that the (positive) effect of income on energy consumption or expenditure dominates the potential decelerating effects of urban form. Hence, if urban incomes in Indonesia continue to rise, future energy consumption in Indonesia is expected to increase substantially, since the vast majority of people in Indonesia prefer to commute by motorcycle. This also implies a substantial increase in future greenhouse gas emissions and local air pollution. This will pose huge challenges in combatting climate change, for which large-scale investments in public transport and electric motorcycles provide promising but costly policy directions.

APPENDIX 5.A – Demographic Characteristics

Table 5.10 – Demographic Characteristics of Cities in Indonesia

		Population		Average Annual Population Growth	Area	Density
		People	People	%	Km²	People/ km²
		2000	2012	2000–12	2012	2012
1	DKI Jakarta	8,360,800	9,862,088	1.38	662	1,489
2	Surabaya	2,618,927	2,805,718	0.57	327	8,585
3	Bekasi City	1,622,207	2,498,598	3.60	210	1,187
4	Bandung City	2,136,260	2,444,617	1.12	167	14,611
5	Jember	786,232	2,367,482	9.19	3,293	719
6	Medan	1,905,587	2,149,114	1.00	265	8,107
7	Tangerang City	1,311,746	1,904,598	3.11	165	11,575
8	Depok	1,120,892	1,891,981	4.36	200	946
9	Cilacap	468,687	1,666,192	10.57	2,139	779
10	Semarang City	1,222,283	1,616,494	2.33	374	4,326
11	Purwokerto (Banyumas)	673,510	1,589,930	7.16	1,328	1,198
12	Banyuwangi	551,572	1,574,528	8.74	5,783	272
13	Palembang	1,201,441	1,513,424	1.92	401	3,778
14	Makassar	1,076,259	1,387,033	2.11	176	7,891
15	Sumenep	136,698	1,056,415	17.04	2,093	505
16	Batam	413,458	1,047,534	7.75	1,648	636
17	Bogor City	746,915	995,081	2.39	119	8,397
18	Pekanbaru	574,551	958,352	4.26	632	1,516
19	Bandar Lampung	736,272	923,175	1.89	197	4,681
20	Padang	598,765	863,401	3.05	695	1,242
21	Malang City	735,919	834,527	1.05	110	7,582
22	Denpasar	520,564	828,926	3.88	128	6,487
23	Kudus	477,475	800,403	4.31	425	1,883
24	Samarinda	465,309	781,313	4.32	718	1,088
25	Watampone (Bone)	89,890	729,516	17.45	4,559	160
26	Tembilahan (Indragiri Hilir)	620,160	676,419	0.72	11,606	58
27	Banjarmasin	518,660	647,403	1.85	98	6,575
28	Singaraja (Buleleng)	214,507	634,308	9.03	1,366	464
29	Balikpapan	380,348	583,272	3.56	508	1,147
30	Pontianak	472,220	577,573	1.68	108	5,357
31	Jambi	400,347	551,714	2.67	205	2,686
32	Surakarta	490,383	505,401	0.25	44	11,476
33	Mataram	318,383	422,673	2.36	61	6,895
34	Bulukumba	394,757	401,897	0.15	1,155	348
35	Yogyakarta	397,398	397,594	0.00	33	12,234
36	Sampit (Kotawaringin Timur)	159,349	395,747	7.58	16,796	24

Table 5.10 – Demographic Characteristics of Cities in Indonesia (continued)

		Population		Average Annual Population Growth	Area	Density
		People	People	%	Km²	People/ km²
		2000	2012	2000–12	2012	2012
37	Cilegon	247,154	391,203	3.83	176	2,229
38	Ambon	168,329	363,771	6.42	359	1,012
39	Kupang City	216,788	358,382	4.19	180	1,988
40	Mamuju	281,500	357,999	2.00	5,054	71
41	Palu	236,123	350,178	3.28	395	886
42	Bengkulu	271,025	326,219	1.54	152	215
43	Bungo	79,708	320,627	11.60	4,659	69
44	Kendari	164,502	313,404	5.37	267	1,172
45	Sukabumi City	243,737	308,405	1.96	484	637
46	Maumere (Sikka)	43,724	306,431	16.23	1,732	177
47	Cirebon City	272,263	298,825	0.78	37	7,999
48	Kediri City	251,522	273,695	0.70	63	4,317
49	Jayapura	146,825	268,285	5.02	940	285
50	Dumai	115,613	268,022	7.01	1,727	155
51	Tegal City	235,443	242,714	0.25	40	6,117
52	Pematangsiantar	241,524	240,432	−0.04	80	3,006
53	Palangkaraya	142,933	236,831	4.21	2,679	88
54	Banda Aceh	216,289	234,517	0.67	61	3,822
55	Tanjung	34,655	227,714	15.69	3,946	58
56	Probolinggo City	159,270	222,292	2.78	57	3,923
57	Merauke	67,872	205,881	9.25	46,792	4
58	Sorong City	89,647	205,684	6.92	1,105	186
59	Ternate	131,334	197,566	3.40	140	1,411
60	Tarakan	111,164	194,285	4.65	251	775
61	Manokwari	106,560	192,487	4.93	14,449	13
62	Gorontalo	119,730	189,476	3.83	79	2,398
63	Pangkal Pinang	122,335	183,794	3.39	118	1,552
64	Meulaboh (Aceh Barat)	133,350	181,886	2.59	2,928	62
65	Madiun City	169,655	172,886	0.16	33	5,203
66	Tanjung Pandan (Belitung)	111,460	163,977	3.22	2,294	71
67	Metro	89,017	151,117	4.41	69	2,198
68	Pare	98,591	133,381	2.52	99	1,343
69	Bukittinggi	91,093	116,075	2.02	25	4,599
70	Sibolga	82,310	85,508	0.32	11	7,939
71	Manado	38,052	41,764	0.78	157	2,656

Source: (1) The population in 2012 is from the Indonesia Database for Policy and Economic Research (World Bank, 2015). (2) Most of the urban population in 2000 is calculated from the percentage of urban population and total population in 2000 from the Indonesia Database for Policy and Economic Research (World Bank, 2015), but some data are from reports of the result of the 2000 population census in some provinces released by Statistics Indonesia in 2001. (3) The area in 2012 is from various official statistical reports by cities, regencies and provinces in Indonesia.

Table 5.11 – Demographic Characteristics of Districts in Yogyakarta Province

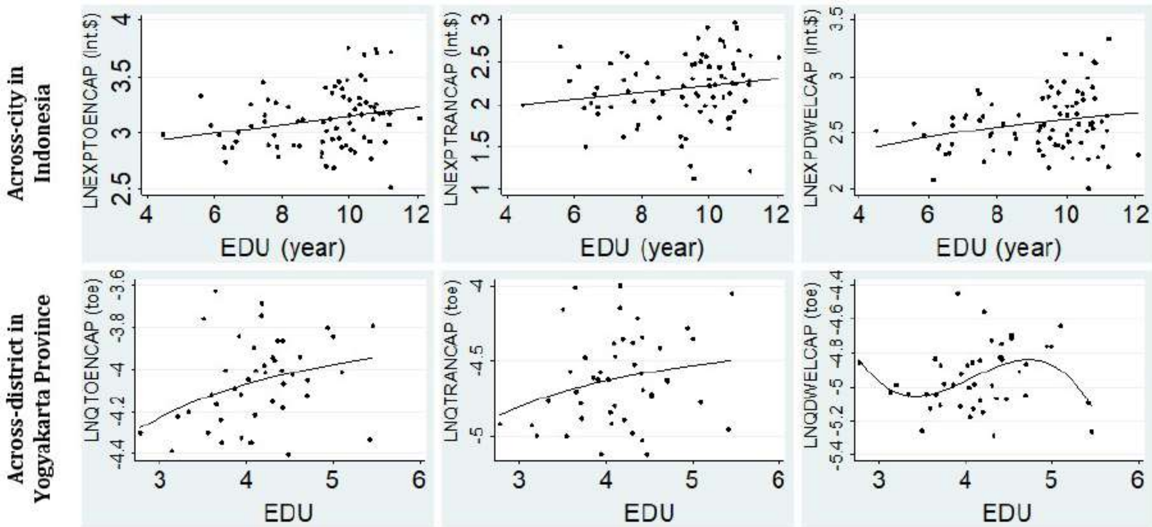
		District	Population		Average Annual Population Growth	Area	Density
			People	People	%	Km²	people/ km²
			2000	2016	2000–16		2016
Yogyakarta	1	Mantrijeron	32,557	33,103	0.10	2.61	12,683
	2	Kraton	19,778	17,564	−0.74	1.4	12,546
	3	Mergangsan	31,378	30,475	−0.18	2.31	13,193
	4	Umbulharjo	69,269	88,667	1.56	8.12	10,920
	5	Kotagede	27,900	36,165	1.63	3.07	11,780
	6	Gondokusuman	48,454	47,160	−0.17	3.99	11,820
	7	Danurejan	19,755	19,019	−0.24	1.1	17,290
	8	Pakualaman	10,593	9,341	−0.78	0.63	14,827
	9	Gondomanan	13,874	13,603	−0.12	1.12	12,146
	10	Ngampilan	17,557	16,932	−0.23	0.82	20,649
	11	Wirobrajan	26,632	25,831	−0.19	1.76	14,677
	12	Gedongtengen	17,857	18,216	0.12	0.96	18,975
	13	Jetis	25,959	23,911	−0.51	1.7	14,065
	14	Tegalrejo	35,148	37,757	0.45	2.91	12,975
Sleman	1	Moyudan	29,071	31,458	0.49	27.62	1,139
	2	Minggir	28,107	29,844	0.38	27.27	1,094
	3	Seyegan	39,201	46,902	1.13	26.63	1,761
	4	Godean	53,862	71,239	1.76	26.84	2,654
	5	Gamping	76,212	107,084	2.15	29.25	3,661
	6	Mlati	79,209	112,021	2.19	28.52	3,928
	7	Depok	158,254	188,771	1.11	35.55	5,310
	8	Berbah	38,224	57,691	2.61	22.99	2,509
	9	Prambanan	41,315	48,395	0.99	41.35	1,170
	10	Kalasan	58,783	85,220	2.35	35.84	2,378
	11	Ngemplak	46,617	65,016	2.10	35.71	1,821
	12	Ngaglik	74,507	117,751	2.90	38.52	3,057
	13	Sleman	52,133	67,201	1.60	31.32	2,146
	14	Tempel	44,076	50,599	0.87	32.49	1,557
	15	Turi	29,124	34,233	1.02	43.09	794
	16	Pakem	28,026	37,733	1.88	43.84	861
Bantul	1	Srandakan	27,180	29,230	0.46	18.32	1,596
	2	Sanden	28,543	30,192	0.35	23.16	1,304
	3	Kretek	26,871	30,285	0.75	26.77	1,131
	4	Pundong	30,042	32,440	0.48	23.68	1,370
	5	Bambanglipuro	35,165	38,366	0.55	22.69	1,691
	6	Pandak	44,604	49,181	0.61	24.3	2,024
	7	Bantul	52,597	62,667	1.10	21.96	2,854
	8	Jetis	46,474	54,670	1.02	24.47	2,234
	9	Pleret	36,947	46,599	1.46	22.97	2,029
	10	Piyungan	38,568	54,392	2.17	32.54	1,672
	11	Banguntapan	88,437	139,258	2.88	28.48	4,890
	12	Sewon	86,414	114,117	1.75	27.16	4,202
	13	Kasihan	86,846	124,667	2.29	32.38	3,850
	14	Pajangan	27,892	35,483	1.52	33.25	1,067
	15	Sedayu	39,575	46,915	1.07	34.36	1,365

Source: (1) The population and area in 2016 are from the Statistics of Yogyakarta Municipality (2017), Statistics of Sleman Regency (2017) and Statistics of Bantul Regency (2017). (2) The total population and urban population in 2000 are from the results of the 2000 population census in Yogyakarta City, Sleman Regency and Bantul Regency (BPS Provinsi DIY, 2013).

APPENDIX 5.B – Scatter Plots for Education and Urbanization versus Energy and for Income versus Urban Area Characteristics

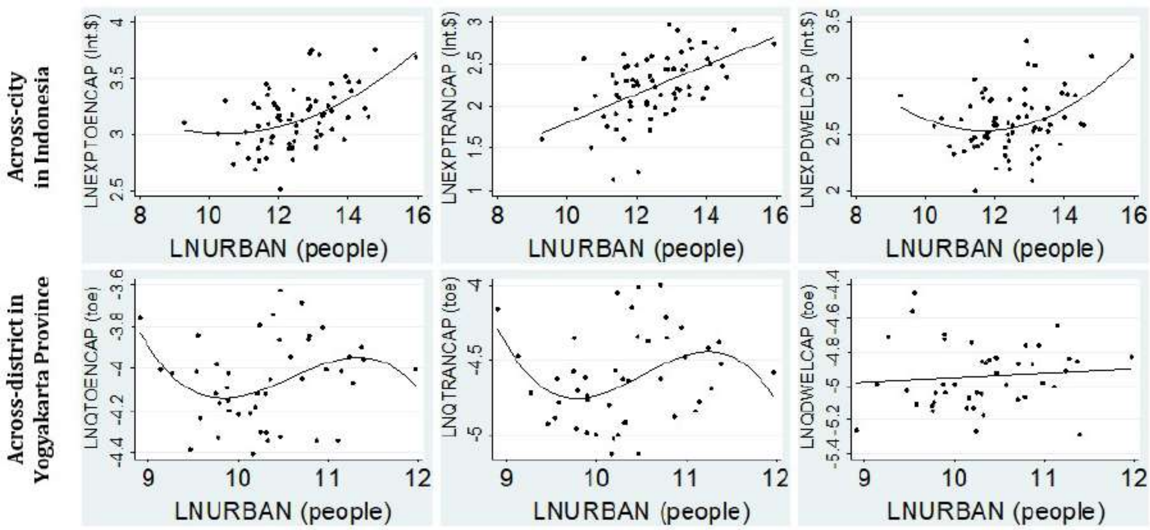
Figures 5.6 and 5.7 show the relationship between per capita energy use and education and urban population successively, both for the cross-city dataset for Indonesia and for the cross-district dataset for Yogyakarta Province.

Figure 5.6 – Plot Showing Energy Use versus Education



Notes: LN = natural logarithm, EXP = expenditure, Q = quantity, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwelling and EDU = mean years of schooling of the population aged 15 years or older (figures at the top) and EDU = average education level attained by household members (figures at the bottom).

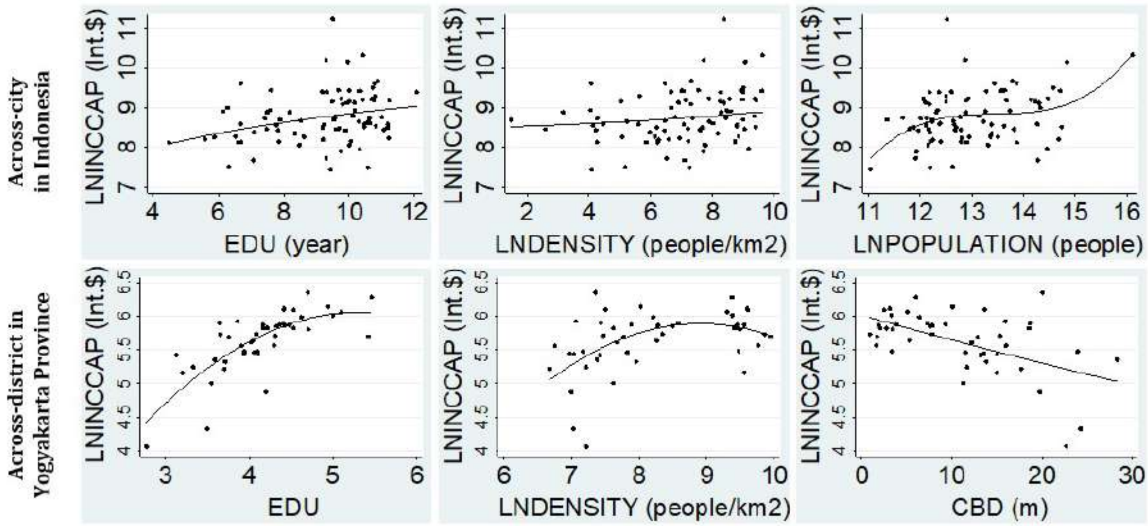
Figure 5.7 – Plot Showing Energy Use versus Urbanization



Notes: LN = natural logarithm, EXP = expenditure, Q = quantity, CAP = per capita, TOEN = total energy, TRAN = energy for transport, DWEL = energy for dwelling and URBAN = historical urban population.

Education seems to have a positive relationship with per capita energy use both across cities in Indonesia and across districts in Yogyakarta Province. Across cities in Indonesia, urbanization also tends to have a positive correlation with the per capita energy expenditure, and, across districts in Yogyakarta Province, urbanization seems to have a non-linear relationship with the per capita energy consumption.

Figure 5.8 – Characteristics between Income and Education, Population Density and Population (Top) and Distance between the Home and the City Centre (Bottom)



Notes: LN = natural logarithm, CAP = per capita, INC = income, EDU = mean years of schooling of the population aged at least 15 years (figures at the top) and EDU = average education level attained by household members (figures at the bottom), DENSITY = population density and POPULATION = city size.

In Figure 5.8, we display the relationship between the per capita income and education and the population density and between per capita income and the population or the distance between the home and the city centre. Education has a positive correlation with the per capita income. The per capita income also tends to have a positive relationship with the population density, but, across districts in Yogyakarta Province, the per capita income seems to decrease after a certain level of population density is reached.

APPENDIX 5.C – Questionnaire of the Survey Conducted in Yogyakarta Province

QUESTIONNAIRE OF HOUSEHOLD ENERGY CONSUMPTION IN YOGYAKARTA CITY, SLEMAN REGENCY AND BANTUL REGENCY

DATE: ____________ 2016 The Questionnaire Number: ___|___|___|___| Name of Interviewer:____________________

BASIC INFORMATION Name of respondent: ____________________ Phone: ____________ Relationship with head of the household: ____________

Regency/City: ____________________ District: ____________________ Village: ____________________

Residency Address: ____

Region classification 1A for the residence area (mark with ×): ☐ Yogyakarta Agglomeration Urban Area Urban ☐ Non Yogyakarta Agglomeration Urban Area Urban

Region classification 2 for the residence area (mark with ×): ☐ Urban ☐ Peri Urban ☐ Rural

PART-I: DATA ON HOUSEHOLD MEMBERS

	Name of Household Members	Sex [L/W]	Age (year old)	Education Attainment	Job/ Occupation
1					
2					
3					
4					
5					

	Name of Household Members	Sex [L/W]	Age (year old)	Education Attainment	Job/ Occupation
6					
7					
8					
9					
10					

Codes for Job:
1. Government Employee
2. Private Employee
3. Entrepreneur
4. Student
5. Housewife
6. Retired
7. Under unemployment
8. Unemployment

Codes for education:
1. No schooling
2. Did Not Complete/Not Yet Completed Elementary School
3. Elementary School/equivalent
4. Junior High School/equivalent
5. Senior High School/equivalent
6. Diploma I/II
7. Diploma III
8. Diploma IV/S1 (Bachelor)
9. S2 (Master)/S3 (Doctoral)

Code for region classification 1B for the main activity: 1. Yogyakarta Agglomeration Urban Area 2. Non Yogyakarta Agglomeration Urban Area

Commuter Characteristics (the order of household members follow the order in the previous table)

Household Members	Current Main Activity (mark with ×)				Location of the Main Activity				
	Working	Study	Shopping	Other	Village	District	Regency/City	Note (detail hint of the location of the main activity)	Region Classification 1B
1									
2									

1

Household Members	Current Main Activity (mark with ✕)				Location of the Main Activity				
	Working	Study	Shopping	Other	Village	District	Regency/City	Note	Region Classification 1B
3									
4									
5									
6									
7									
8									
9									
10									

PART-II: DATA ON TRANSPORTATION MODES USED BY HOUSEHOLD

A. TRANSPORT MODE USED BY HOUSEHOLD

Depart to/return from the main activity (the order of household members follow the order in the previous table; mark with ✕ for Transport mode, Frequency and Travel Time)

Household Members	How many transport modes do you use in the trip?	Transport Mode												Frequency Trip (times/week)				Travel Time (minutes)							Travel Distance (km)
		Bus/ Minibus	Train	Taxi	Motorcycle Taxi	Pedicab	Horse-pulled cart	Subscription of School Car Shuttle	Service of Office Car/ Bus Shuttle	Private/ Offive Car	Private/ Offive Motorcycle	Bicycle	Walking	≤ 2	3 – 4	5 – 6	> 6	≤ 20	> 20 – ≤ 30	> 30 – ≤ 45	> 45 – ≤ 60	> 60 – ≤ 90	> 90 – ≤ 120	> 120	
1																									
2																									
3																									
4																									
5																									
6																									

2

Household Members	How many transport modes do you use in the trip?	Transport Mode												Frequency Trip (times/week)				Travel Time (minutes)							Travel Distance (km)
		Bus/ Minibus	Train	Taxi	Motorcycle Taxi	Pedicab	Horse-pulled cart	Subscription of School Car Shuttle	Service of Office Car/ Bus Shuttle	Private/ Offive Car	Private/ Offive Motorcycle	Bicycle	Walking	≤ 2	3 – 4	5 – 6	> 6	≤ 20	> 20 – ≤ 30	> 30 – ≤ 45	> 45 – ≤ 60	> 60 – ≤ 90	> 90 – ≤ 120	> 120	
7																									
8																									
9																									
10																									

Transportation mode for **leisure** (the order of household members follow the order in the previous table; mark with × for Transport mode, Frequency and Travel Time)

Household Members	How many transport modes do you use in the trip?	Transport Mode										Frequency Trip (times/week)				Travel Time (minutes)							Travel Distance (km)
		Bus/ Minibus	Train	Taxi/Rent a Car	Motorcycle Taxi	Pedicab	Horse-pulled cart	Private/ Offive Car	Private/ Offive Motorcycle	Bicycle	Walking	≤ 2	3 – 4	5 – 6	> 6	≤ 20	> 20 – ≤ 30	> 30 – ≤ 45	> 45 – ≤ 60	> 60 – ≤ 90	> 90 – ≤ 120	> 120	
1																							
2																							
3																							
4																							
5																							
6																							
7																							
8																							
9																							
10																							

B. PUBLIC TRANSPORTATION

Househol expenditure per month for public transportation/non private vehicles (IDR): ____________________

Notes: ____________________

____

C. PRIVATE/OFFICE VEHICLES

Do you use your private vehicle in your work or in your business?

☐ No ☐ Yes, explain: ____________________

____

Private vehicle owned by household and household fuel consumption per month (mark with × for yes/no question):

	Vehicle Type	Ownership		Quantity (unit)	Gasoline Consumption		Diesel Consumption		Notes
		YES	NO		Litre	IDR	Litre	IDR	
1	Private Car								
2	Motorcycle								
3	Bicycle								

Car characteristics (mark with × for car and fuel type):

	Car Type by Maximum Number of Passengers (Including the Driver)				Fuel Type		Car Age (year old)	Usage (year)	Notes
	Pick Up	Passenger Cars			Gasoline	Diesel			
		4 − 5	6 − 8	≥9					
1									
2									
3									
4									
5									

4

PART-III: DATA ON THE UTILIZATION OF ELECTRICITY AND FUEL FOR COOKING BY HOUSEHOLD

Do you have any business in your residence? ☐ NO ☐ YES, explain: ____________

A. **INFORMATION ABOUT DOMESTIC ENERGY** (mark with ×):

	Type of Energy/ Electric Appliance	YES	NO	If YES (in years)			
				≤2	>2 – ≤5	>5 – ≤10	>10
1	Using electricity						
2	Using Air Conditioner						
3	Using gas stove						
4	Cooking with charcoal/charcoal briquette						
5	Cooking with biomass (firewood)						
6	Using electricstove						
7	Using kerosene stove						
8	Other, mention:						

B. **QUANTITY AND VALUE OF ENERGY USED BY HOUSEHOLD**

	Type of Energy	Quantity	Unit	Expendidure (IDR/month)	Notes
1	Electricity		kWh		
2	Gas (LPG)		units of 3 kg tube		
			units of 5.5 kg tube		
			units of 9 kg tube		
			units of 12 kg tube		
			units of 14 kg tube		
3	Charcoal/ charcoal briquette		kg		
			sack		1 sack = kg
4	Biomass (Firewood)		bundles		1 bundle = kg
5	Kerosene		litre		
6	Other, mention:				

5

PART-IV: DATA ON THE RESIDENCE AND LOCATIONS

A. CHARACTERISTICS OF THE RESIDENCE (mark with ✕):

☐ Apartment ☐ House ☐ Rent Room ☐ Other, mention: ____________

Status: ☐ Rent ☐ Free to stay without rent ☐ Private Property

If private property: ☐ own build ☐ purchased in year: ________

How many years have you live in your residence: ☐ ≤ 2 years ☐ > 2 – ≤ 5 years ☐ > 5 – ≤ 10 years ☐ > 10 years

Number of bed rooms in the house: ☐ ≥ 4 rooms ☐ 2 – 3 rooms ☐ 1 room

Building area of the residence: ________ m^2 Land area of the residence: ________ m^2 How many floors are in your residence? ________

B. DISTANCE FROM THE RESIDENCE TO SOME LOCATIONS

How far is your residence from:

	Location	Distance (m)	Travel Time (minutes)	Note for Travel Time	Note (hint for the location or how to buy the LPG, by order/not, etc.)
1	The nearest main road			By walking/car/motorcycle/public transportation	
2	The nearest place where you can get a public transportation			By walking/car/motorcycle/public transportation	
3	The nearest gasoline/diesel station			By walking/car/motorcycle/public transportation	
4	The nearest gas (LPG) sales shop			By walking/car/motorcycle/public transportation	
5	The nearest charcoal/briquette sales shop			By walking/car/motorcycle/public transportation	
6	The nearest biomass (firewood) sales shop			By walking/car/motorcycle/public transportation	
7	The nearest kerosene sales shop			By walking/car/motorcycle/public transportation	

PART-V: DATA ON HOUSEHOLD INCOME

HOUSEHOLD INCOME (million IDR) (mark with ✕): ☐ < 1.3 ☐ 1.3 – < 2.6 ☐ 2.6 – 6 ☐ > 6 – 10 ☐ > 10 – 20 ☐ > 20

6

CHAPTER 6 Does Urban Form Affect Transport Mode Choice? Evidence from Yogyakarta, Indonesia[41]

6.1 Introduction

We analyse the way in which urban form influences preferences for the use and ownership of motorcycles, using the results from a field study conducted in the metropolitan area of Yogyakarta in Indonesia. Across all of Asia, the number of motorcycles in urban road traffic is much higher than the number of passenger cars – as shown in Table 6.1. Almost 80% of the world's motorcycles can be found in Asia (ITF, 2008). This popularity can be explained by their relatively low price and maintenance costs (Hsu et al., 2003), their relatively easy parking options and their higher average speed in congested cities in combination with the local climate conditions. Many governments in Asian countries have been trying to encourage people to reduce their usage of private motorized vehicles and to change to public transportation or non-motorized transport modes to decrease the energy consumption and emissions from transport. However, it will not be an easy goal to achieve, because, as we found in Chapter 5, the per capita income has a positive effect on energy use. When people's income increases, a motorcycle will become a potential option, especially for people who live far from the city centre (in less dense areas), because we also found that those people tend to have a long commuting distance.

In a few decades from now, the world's urban population will be larger than the entire current global population (United Nations, 2015). Urban areas already account for half of the world's population, generate around 80% of the global gross domestic product (GDP) and are associated with around 70% of the global energy consumption and energy-related emissions. Road transport is a major source of energy-related nitrogen oxide emissions and primary particulate matter. Because cities are concentrations of people, economic activity, energy use and traffic, they tend to experience the most harmful concentrations of air pollution. Each year, 6.5 million

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deaths can be attributed to air pollution, which, according to the World Health Organization (WHO), is much more than the number of deaths from HIV/AIDS, tuberculosis and road injuries combined (Hutt & Breene, 2016). In urban areas, individual exposure to vehicle-generated pollutants is often higher, on average, than exposure to other sources, because emissions from pipes or road vehicles are close to the ground and therefore close to people (IEA, 2016).

Table 6.1 – Motorcycle Statistics for Asian Countries

Country	% of Households Owning a Motorcycle [1]	# of Motorcycles per 1,000 People[2,3]	# Motorcycles as % of Total Vehicles[2]
Vietnam	86	422	95
Indonesia	85	345	83
Thailand	87	286	59
Malaysia	83	373	47
India	47	92	72
China	60	69	38
Pakistan	43	31	61
Philippines	32	43	55
Bangladesh	18	9	64
Japan	21	94	13
South Korea	9	43	9

Data Sources: (1) Percentage of households that owned a motorcycle or scooter in 2014 (Pousther, 2015). (2) Number of motorized two and three wheelers and total number of registered vehicles (WHO, 2015). (3) The population is from the World Development Indicators (World Bank, 2016). The year for (2) and (3) is 2012 or 2013, except for Pakistan (2011) and Bangladesh (2014).

Low- and middle-income countries, especially in Asia, play a key role in these matters. Until 2050, around 90% of the global urban population growth will take place in low- and middle-income countries. By 2050, around 80% of the total urban population is expected to live in cities in low- and middle-income countries, with Asia housing more than 50% of the total urban population (United Nations, 2015). In terms of the GDP, at present, low- and middle-income countries account for more than two-fifths of the world GDP and for most of the economic growth, with the Asia-Pacific region as the leader for global growth. As a result, especially urban areas in Asia have experienced a rapid increase in the number of registered passenger cars and motorcycles over the last decade – thus causing road traffic to be a significant source of air pollution and greenhouse gas emissions in Asian cities.

Many studies on transport mode choice have considered the urban form as a potentially relevant explanatory variable (Asensio, 2002; Dieleman et al., 2002; Bento et al., 2005; Limtanakool et al., 2006; Buehler, 2011; Clark et al., 2016; Sun et al., 2017) because of the idea that a compact urban area may reduce the usage of private motorized vehicles, given that a high urban density implies shorter travel distances to people's workplace, school or shopping areas and better conditions to provide good public transportation facilities (Dieleman & Wegener, 2004; Neuman, 2005). Some studies have indeed found that the population density or population size has a statistically negative effect on the energy consumption or emissions from transport (Newman & Kenworthy, 1989; Banister et al., 1997; Mindali et al., 2004; Glaeser & Kahn, 2010).

Transport mode studies for Europe or the United States have mostly investigated the factors that affect people's preferences for the ownership and use of private cars in comparison with the use of public transport (bus and/or train) and/or non-motorized transport modes (cycling and/or walking) (Van Vugt et al., 1996; Asensio, 2002; Dieleman et al., 2002; Van Wee et al., 2002; Bento et al., 2005; Limtanakool et al., 2006; Buehler, 2011; Clark et al., 2016; Heinen, 2016). In addition, preferences for motorcycle use have been studied from a mode choice perspective (Sheikh et al., 2006; Chen & Lai, 2011; Irawan & Sumi, 2011a; Putra, 2013; Liu et al., 2016; Marquet & Miralles-Guasch, 2016). However, to the best of our knowledge, in these studies, the role of the urban form has remained underexposed.

Table 6.2 – Population (Density), GRDP and Private Motor Vehicles across Java Island in 2016

Provinces	Population (Thousands)	Population Density (People/km²)	Per Capita GRDP (Million IDR)	Registered Private Motor Vehicles per Thousand People				
				Ratio Motorcycle to Car	Levels 2016		Total Growth 2005–2016 (%)	
					Motorcycle	Car	Motorcycle	Car
D.I. Yogyakarta	3,720.9	1,188	29.6	10.1	923	92	25.14	28.13
DKI Jakarta	10,277.6	15,478	211.8	4.0	1438	363	91.05	52.44
West Java	47,379.4	1,341	34.9	6.2	177	29	100.04	96.32
Central Java	34,019.1	1,037	32.1	12.6	402	32	57.41	95.03
East Java	39,075.3	817	47.5	9.6	346	36	43.13	33.79
Banten	12,203.1	1,263	42.3	15.6	203	13	210.01	61.13

Data Source: Statistics Indonesia (2009, 2017).

We help to fill this gap by studying how the urban form influences preferences for the use and ownership of motorcycles in an urban area relative to other transport modes and road vehicles. To achieve this aim, we conducted a field study in the metropolitan area of Yogyakarta in Indonesia, part of D.I. Yogyakarta Province. Located on the island of Java, urban Yogyakarta is a typical medium-sized city in Indonesia, with an estimated population of 2.6 million and a population density of 2,317 inhabitants per square kilometre.[42] The urban area features over 900 registered motorcycles per 1000 people, which is the second-highest rate in Java (after the Indonesian capital city of Jakarta) and 10 times more than the number of registered passenger cars – see Table 6.2.

Several studies on commuting behaviour in Indonesia have been conducted. Most of these studies have described the characteristics of commuters and their travel behaviour (Leinbach & Suwarno, 1985; Sitanala, 2005; Bandono, 2010; Ismardani, 2010; Batti, 2011; Adhi, 2012; Ansusanto et al., 2012; Pebrian & Ratnasari, 2013; BPS Kota Bekasi, 2015; BPS Provinsi DKI Jakarta, 2015). To the best of our knowledge, only the studies by Irawan and Sumi (2011a, 2011b), Yagi et al. (2012; 2014) and Putra (2013) explicitly studied the factors that affect transport modes and only Yagi et al. (2014) studied the factors that influence car or motorcycle ownership. The latter two studies were also carried out in Yogyakarta Province. In investigating the factors that influence preferences for transport modes, Irawan and Sumi (2011a, 2011b) focused on the commuting behaviour of students whereas Putra (2013) focused on workers. We capture not only work and study activities but also shopping and other regular activities and leisure activity.

The structure of this chapter is as follows. In section 6.2, we present a brief review of the literature on transport mode choice. In section 6.3, we describe our regression methodology. Section 6.4 presents our data and descriptive statistics. Section 6.5 then provides the results of our regression analyses. Section 6.6 concludes.

6.2 Literature Review

Many studies have been conducted to understand the factors that influence transport mode choice (for example, Van Vugt et al., 1996; Asensio, 2002; Dieleman et al., 2002;

[42] D.I. Yogyakarta Province consists of Yogyakarta City, Sleman Regency, Bantul Regency, Kulon Progo Regency and Gunung Kidul Regency. The research was conducted in Yogyakarta City and two regencies that surround Yogyakarta City, specifically Sleman Regency and Bantul Regency. The total population and population density were calculated for the research area. Yogyakarta City and some districts in Sleman Regency and Bantul Regency are also known as the Yogyakarta Urban Agglomeration area.

Van Wee et al., 2002; Limtanakool et al., 2006; Sheikh et al., 2006; Müller et al., 2008; Buehler, 2011; Chen & Lai, 2011; Irawan & Sumi, 2011a; Yagi et al., 2012; Heinen et al., 2013; Yagi et al., 2014; Marquet & Miralles-Guasch, 2016; Sun et al., 2017). This literature leads us to classify the factors that influence the preferences for transport mode and car or motorcycle ownership into seven groups: (1) travellers' personal and household characteristics; (2) travel characteristics; (3) type of travel activity or purpose of travel activity; (4) factors related to the urban form; (5) factors related to the climate; (6) psychological factors; and (7) work facilities related to the transport mode. Our survey did not cover information related to the last three groups. Therefore, we focus our study on the first four groups of factors: we aim to explain the use and ownership of motorcycles from travel characteristics, urban form and type of travel activity while using personal and household characteristics as control variables. In the remainder of this section, we provide a literature review with a focus on the variables that we use in our analysis.

6.2.1 Modal Choice

Most studies have focused on the transport mode choice of workers (Van Vugt et al., 1996; Asensio, 2002; Bento et al., 2005; Heinen et al., 2013; Putra, 2013; Clark et al., 2016; Sun et al., 2017). Some studies have investigated the transport mode preferences of travellers but have not differentiated their study by types of travel activity (Van Wee et al., 2002; Chen & Lai, 2011; Heinen, 2016; Liu et al., 2016; Sheikh et al., 2006). Other studies have focused on the travel behaviour of students (Müller et al., 2008; Irawan and Sumi, 2011a). Various studies have differentiated their models based on different travel activities. Dieleman et al. (2002), in their models, distinguished trips for shopping, work and leisure activities. Limtanakool et al. (2006) distinguished different models for commuting trips, business trips and trips made during leisure time. Yagi et al. (2012, 2014) grouped their models based on work and study activities.

Models that are separated by trip purposes allow us to examine whether the same factor has different effects on the transport choice for all trip purposes. However, comparing the results from many different models is difficult. A simpler method is to include the trip purpose as an explanatory variable. For example, Buehler (2011) used work and shopping activities, and Marquet and Miralles-Guasch (2016) included work/study, shopping and returning home activities as independent variables. These studies employed multinomial logistic models. By including trip purposes in the model, they had to exclude one of the trip purposes – for example, leisure activity – from the model and use it as a reference. Marquet & Miralles-Guasch (2016) discovered that trip purposes have a very limited influence on transport mode choice. However, Buehler (2011) found that work activity increases the probability of using a car rather than cycling or walking but decreases the probability of taking the car when compared with public transportation. He also discovered that, in the United States, shopping activity raises the tendency to use a car, while the opposite is true for Germany, where shopping activity decreases the chance of choosing a car compared with public transportation and non-motorized transport modes. This underlines the importance of cross-country differences in explaining the variation in study outcomes.

6.2.2 Travel Characteristics

In our analysis, we define travel characteristics only in terms of travel distance (see the next section). Travel distance, of course, is a key factor in transport mode choice studies. Dieleman et al. (2002) and Scheiner (2010) showed that travellers who choose to walk have a short travel distance, travellers who ride a bicycle have a medium-short travel distance, travellers who use public transportation have a medium-high travel distance and travellers who travel by car have a long travel distance.

For commuters, a longer travel distance in general reduces the probability of taking the bus compared with the train (Asensio, 2002), has a significantly negative effect on cycling and/or walking (Heinen et al., 2013; Clark et al., 2016) and has a significantly positive effect on car use (Clark et al., 2016). Marquet and Miralles-Guasch (2016) found that a long travel distance increases the likelihood that travellers will choose a motorcycle over a car, public transportation or a non-motorized transport mode. More specifically, they found that, on average, an increase in the travel distance by 1 kilometre increases the probability of travelling by motorcycle by 25.6%, decreases the probability of travelling by car by 8.5% and reduces the probability of travelling by public transportation or non-motorized transport mode by 17.1% (Marquet & Miralles-Guasch, 2016).

Müller et al. (2008) found that students with a long travel distance have a higher probability of travelling by car or motorcycle than by public transport, walking or cycling. Irawan and Sumi (2011a) discovered that adolescent students with a long travel distance have a higher tendency to travel to and from school by riding a motorcycle by themselves rather than by walking or cycling. Younger students with a long travel distance have a higher likelihood of being escorted to and from school than walking or cycling by themselves and have a higher probability of being escorted from school than going home by bus by themselves.

6.2.3 Urban Forms

The bid–rent model by Alonso explains that families will choose houses in locations that they can afford with their budget (Neuman, 2005), so there is a tendency for commuters from high-medium-income households to live near the city centre and have a shorter commuting distance, whereas commuters from medium-low-income households live far from the city centre and have a longer commuting distance. However, according to Glaeser et al. (2008), in the US, poor people have to live around the city centre because they must depend on the public transportation, which is more available in the city centre, whereas wealthy people who can afford a car can live in an area far from the city centre.

In Indonesia, high-income people might also looking for residences in peri-urban areas because it is not easy to find available residences around the city centre, especially if they want wide land or a large house. The land prices around the city centre, which are high and keep increasing (Suparmono, 2012; Elmanisa et al., 2017), make it difficult for people with a medium-low income to afford a residence around the city centre. Commuters with a medium-low income who live far from the city centre might choose to travel by motorcycle, which is suitable for a long or medium travel distance and their budget.

Many studies have found that population density has a significantly positive effect on the use of public transportation and non-motorized transport modes (Asensio, 2002; Limtanakool et al., 2006; Buehler, 2011; Clark et al., 2016; Sun et al., 2017). Bento et al. (2005) found that population density reduces the likelihood of having one or two cars. An increase in the population density of 1% decreases the probability of having one or two cars by 0.1% and 0.15%, respectively. However, Bento et al. (2005) also found that a 1% increase in the population density reduces the probability of commuters taking the bus by 2.7%.

In general, there is a relatively high negative correlation between the population or household density and the distance from the household residence to the city centre (Muniz & Galindo, 2005; Larson & Yezer, 2015). Thus, the distance from the household residence to the city centre should have the opposite effect on the transport choice mode to the population density. Among the studies on transport mode choice that we reviewed, we only found one study that examined a similar variable to the distance from the household residence to the city centre. Sun et al. (2017) discovered that the distance from home to the primary office complex in the city has a positive impact on the preference for travelling by car.

Dieleman (2002) and Clark et al. (2016) found evidence that the type of residential area influences the transport mode choice. For the Netherlands, Dieleman (2002) identified whether a traveller lives within or outside the economic centre of the country (Randstad area), within the three largest cities (Amsterdam, Rotterdam and the Hague), medium-sized cities, new towns and suburb or rural communities. Areas outside the Randstad were divided into medium-sized cities and suburban or rural communities. He found that, compared with people who live in one of the three largest cities, people who live in other areas have a higher probability of travelling by car, cycling or walking than using public transportation. Limtanakool et al. (2006) obtained similar results. People who live in suburban or less urbanized areas in the rest of the Netherlands are more likely to travel by car than by train. In the United Kingdom, Clark et al. (2016) determined whether commuters live in inner or outer London, other metropolitan areas, urban areas or rural areas. Compared with commuters who live in rural areas, those who live within either inner or outer London have a lower probability of travelling by car, cycling or walking, but commuters who live in urban areas have a higher likelihood of cycling or walking.

The distance from home to a public transportation stop or station can be used to represent the government policy on transport (Buehler, 2011). The longer the distance to reach public transportation, the more reluctant a traveller tends to be to use public transportation and the more interested he/she is in using a private motor vehicle. In Spain, Asensio (2002) found that the distance from home to public transportation increases the likelihood of using a car instead of public transportation.

For the United States, Buehler (2011) attained a similar result but only when the distance from home to public transportation is between 400 and 1000 metres. When the distance from home to a public transportation stop or station is less than 400 metres, travellers are most likely to walk. He found a similar result for Germany, where the distance from home to a public transportation stop is up to 1,000 metres.

6.3 Regression Methodology

To study how the urban form influences people's preferences for the use of motorcycles, we employ a multinomial logistic (MNL) regression model as follows:

$$ln\left(\frac{P_{iml}}{P_{kml}}\right) = \alpha_{0im} + \alpha_{1im}X_{1iml} + \alpha_{2im}X_{2iml} + \alpha_{3im}X_{3im} + \alpha_{4im}X_{4iml} \qquad (6.1)$$

where P_{iml} is the probability that traveller l chooses transport mode i (bus, car, bicycle and walking) for activity m (commuting and leisure) compared with transport mode k (motorcycle), P_{kml} is the probability that traveller l chooses transport mode k for activity m over transport mode i, X_{1iml} is a set of household characteristics of traveller l using transport mode i for activity m, X_{2iml} is a set of travel activities of traveller l using transport mode i for activity m, X_{3iml} is a set of travel characteristics of traveller l using transport mode i for activity m, X_{4iml} is a set of urban form variables in the living area of traveller l who uses transport mode i for activity m, α_0 is a constant and α_{1im}, α_{2im}, α_{3im} and α_{4im} are the regression coefficients.

The household characteristics contain the percentage of female household members, the average age of household members, the average education level attained by household members, the average income of household members, the household size, the number of young children (younger than 7 years) in the household, the number of older children (7–16 years old) in the household, the number of motorcycles or cars owned by the household and the number of bicycles owned by the household. The travel activities are work, study and shopping. The travel characteristics include the travel distance and travel frequency for commuting and leisure activities. The urban form is described by the distance from home to the central business district, the population density in the district[43] where the household

[43] A city or a regency consists of some administrative areas called districts.

lives, whether a household lives in an urban area, whether a household lives in a rural area, the distance from home to the closest or most accessible public transportation station and the distance from home to the closest or most accessible fuel station.

We present the results of this MNL regression approach in terms of the relative risk ratio (*RRR*) and the marginal effects. The *RRR* is defined as $e^{\alpha_{tim}}$, $t = 1, 2, 3, 4$, with α_{tim} being the regression coefficient obtained from equation (6.1). When motorcycle is the reference category, the *RRR* value shows the ratio of the probability that transport mode *i* will be preferred relative to the probability that the motorcycle (k) will be chosen. An *RRR* that is lower than one represents a negative effect of the explanatory variable. An increase in the explanatory variable by 1 unit decreases the *RRR* by $(1 - RRR) \times 100\%$, keeping other variables constant. On the other hand, an *RRR* that is higher than 1 represents a positive effect of the explanatory variable. An increase in the explanatory variable by 1 unit increases the *RRR* by $(RRR - 1) \times 100\%$, keeping other variables constant.

In the MNL regression, holding other explanatory variables constant, the marginal effect for transport mode category *m* demonstrates the average probability that a traveller uses transport mode category *m* or *k* if an explanatory variable increases by one unit. For a dummy variable, the marginal effect shows the change in the probability that a traveller uses transport mode category *m* if the criterion in the dummy variable is fulfilled.

To study how the urban form influences the preferences for the ownership of motorcycles, we employ an ordinal logit regression (OLR) approach as follows:

$$P(Y = criterion1) = P(S + u \leq cut1) = \frac{1}{1+e^{-(cut1-\ )}} \quad (6.2.1)$$

$$P(Y = criterion2) = P(cut1 < S + u \leq cut2) = \frac{1}{1+e^{-(cut2)}} - \frac{1}{1+e^{-(cut1-S)}} \quad (6.2.2)$$

$$P(Y = criterion3) = P(cut2 < S + u \leq cut3) = \frac{1}{1+e^{-(cut3-S)}} - \frac{1}{1+e^{-(cut2)}} \quad (6.2.3)$$

$$P(Y = criterion4) = P(cut3 < S + u) = 1 - \frac{1}{1+e^{-(cut3-\ )}} \quad (6.2.4)$$

with:

$$S = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \quad (6.2.5)$$

where P is a probability, Y is an ordinal variable of motor vehicle ownership where j consists of motorcycle ownership (0 units, 1–2 units, 3–4 units or 5–7 units) or car ownership (0 units, 1 unit, 2 units or 3–4 units), X_1 is a set of household characteristics, X_2 is a set of travel activities, X_3 is a set of travel characteristics, X_4 is a set of urban form variables, u is an error term, β_{1j}, β_{2j}, β_{3j} and β_{4j} are the coefficients and $cut1$, $cut2$ and $cut3$ are constants that can be used to determine the changes among categories.

We present the results of this OLR regression approach in terms of the odds ratio and the marginal effects. The obtained regression coefficients of the OLR model equal the natural logarithm of the odds ratio or $ln\left(\frac{P(Y \leq i)}{P(Y > i)}\right)$. A positive regression coefficient implies an odds ratio larger than one; a negative regression coefficient implies an odds ratio smaller than one. In the OLR approach, holding other explanatory variables constant at their mean value, the difference between the odds ratio coefficient and one (1) represents the change in the odds ratio, that is, the change in the ratio between the success and the failure probabilities, where success represents a household that has private motor vehicle ownership belonging to category[44] *n* or lower and failure reflects a household that has private motor vehicle ownership belonging to a category higher than *n*. The marginal effect for private motor vehicle ownership category *n* shows the average probability that a household has private motor vehicle ownership belonging to category *n* if the explanatory variable increases by one point.

In both regression models, we use the same explanatory variables. However, because the MNL model of transport mode choice uses individual data while the OLR model of motor vehicle ownership uses data at the household level, we adjust some explanatory variables accordingly.

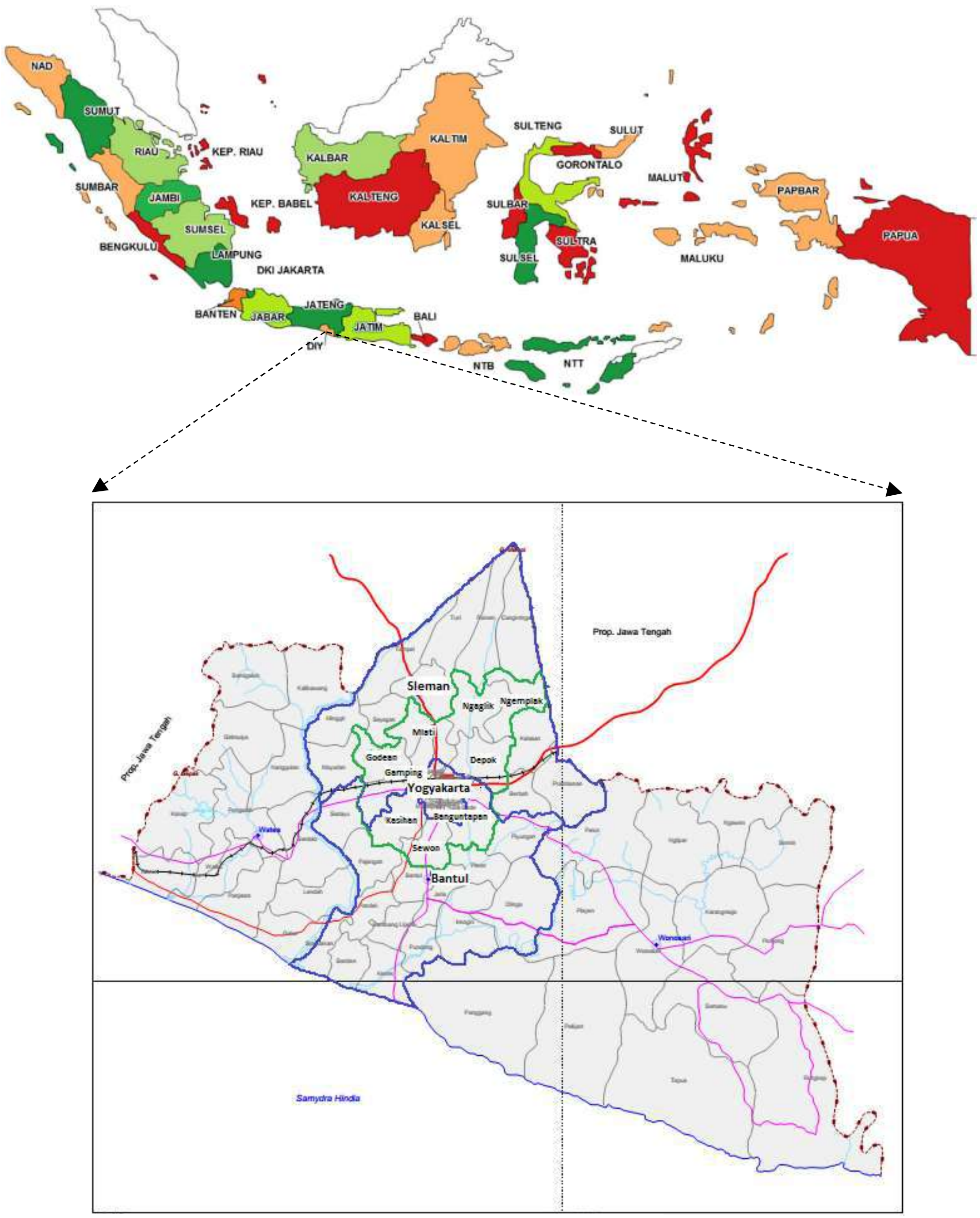
6.4 Data and Descriptive Statistics[45]

Our data were collected through a survey of energy consumption and travel behaviour in the metropolitan area of Yogyakarta, on the island of Java in Indonesia, in 2016. More specifically, we surveyed 823 household in the areas of Yogyakarta City, Sleman Regency and Bantul Regency (see Figure 6.1). Those three areas were chosen because

[44] The categories of motorcycle ownership are 0 units, 1–2 units, 3–4 units and 5–7 units. The categories of car ownership are 0 units, 1 unit, 2 units and 3–4 units.
[45] The data in this study come from the same survey that we used in our study in Chapter 5. In that survey, we collected not only households' energy consumption but also household members' commuting behaviour, including their transport mode preferences.

of their urban character, defined in terms of a relatively high population density and per capita GRDP (see Table 6.3).

Figure 6.1 – Map of Indonesia and Yogyakarta Province



Note: Yogyakarta is known as DIY Province. The blue line marks the border of Yogyakarta City, Sleman Regency and Bantul Regency, and the green line shows the border of districts in Yogyakarta Urban Agglomeration Area. Source: the map of Yogyakarta Province is from Dinas PUP-ESDM DIY (2015), and the map of Indonesia is from https://www.pinterest.com.au/pin/672936369293684236/

Table 6.3 – Demography and Economics in DIY Province in 2015

		City/Regency					
		Yogyakarta	Sleman	Bantul	Kulon Progo	Gunung Kidul	TOTAL
Area[a)] (km^2)	km^2	32.5	574.82	506.85	586.27	1,485.36	3,185.80
Population[1,a)]	people	412,704	1,167,481	971,511	412,198	715,282	3,679,176
Population Density	people/km^2	12,699	2,031	1,917	243	482	1,154.87
Population Growth 2010–15[a)]	% per year	1.27	1.13	1.32	1.12	1.09	1.19
GRDP[b)] (billion IDR)	billion IDR	26,798	33,827	19,325	7,672	13,799	101,425
GRDP per capita	000 IDR	64,933	28,974	19,892	18,612	19,292	27,567
Head of Household[2,c)]	#	128,873	348,781	299,944	-	-	777,598
Sample of Household	#	151	413	259	-	-	823

Notes: (1) Population Projection by Regency/City in D.I.Yogyakarta Province 2010-2020. (2) Number of head of household in semester 2 of 2015, (3) Population Density = Population/Area, (4) GRDP per capita = GDRP/Population.
Source: (a) Statistics of D.I. Yogyakarta Province (2017), (b) Population and Civil Registration Office (Biro Setda Tapem DIY, 2015).

In our survey, we employed the definition of commuting by BPS Provinsi DKI Jakarta (2015). However, we modified the commuting characteristics as defined by Mantra (2000) and BPS Provinsi DKI Jakarta (2015) in several ways. First, we assume that commuting activity is not limited or defined by administrative borders. The reason is that applying administrative borders is likely to lead to incorrect identification of commuters, depending on their travel route and location relative to the administrative border. Second, we do not assume that a commuter always returns home on the same day; rather, we assume that the activity must be carried out within 24 hours.[46] The average commuting distance is defined as the one-way travel distance from a household's residence to the location of the main activity of a household member – assuming that he or she follows the same route on the way home. In the survey, a commuter is defined as a household member who regularly travels to the location of his or her main activity, such as work, study, shopping and so on, and then returns home within 24 hours. The questionnaire of the survey is displayed in the Appendix in Chapter 5.

Travellers for commuting and leisure activities may have different transport modes to travel to and return from the location of their activity. However, for simplification, we only questioned the respondents about the transport modes used to reach the activity location and assumed that most travellers use the same transport mode to return home. A commuter could have more than one regular activity, such as escorting children to school and working, working and shopping, studying and working or having more than one job. For practical reasons, we only recorded the dominant commuting activity. For example, if someone always escorts his children to school besides working, we chose working as the main activity. If an individual has more than one job, we chose to include the job with the highest travel frequency and the longest travel distance and time. If a commuter makes use of more than one transport mode, we included the main transport mode. For example, many bus users must also walk to the bus stop, but, in these cases, we defined the bus as the main transport mode.

[46] In the survey, we found a case in which someone regularly travels late at night to reach a market in another regency early in the morning and then goes home in less than 24 hours to sell the merchandise bought from the market to the sellers in the home neighborhood.

To measure the distance from a household's residence to the city centre, we identified as the city centre the Malioboro region in Yogyakarta. Typically, the city centre – also known as the urban core, the CBD (central business district) or the civic centre (Damayanti & Handinoto, 2005) – is the area in a city where one can find a concentration of political power, cultural manifestations, historic sites, business and financial services, shopping facilities and entertainment. The Malioboro region is home to the office centre of the Governor of Yogyakarta Province, the branch office of the Central Bank of Indonesia, the biggest traditional market in Yogyakarta, named Beringharjo, and the historic Vredeburg Fortress. Malioboro is also the famous tourism region of Yogyakarta and is near Yogyakarta Palace, an important symbol of Javanese culture. Malioboro has been referred to as the city centre by other researchers (Damayanti & Handinoto, 2005; Sugiyanto et al., 2011; Utari, 2015). The distance between a household's residence and Malioboro was estimated using Google Maps and the respondent's address.

We employ both the travel distance and the travel frequency as travel characteristics in our analysis. We exclude the travel time from the models, because some respondents could not estimate their travel time; in these cases, we had to estimate their travel time based on the travel distance, implying a high correlation between the two variables. We decided not to differentiate the models of transport mode choice in commuting activity based on the type of activity or the purpose of travel. Instead, we include three types of commuting activity as explanatory variables, specifically work, study and shopping activities, while using other commuting activity as the reference. Other commuting activity is a routine activity completed within 24 hours that cannot be classified as a work, study or shopping activity. People who are categorized into this group are, for example, persons who have retired and have routine exercise scheduled or persons who regularly undergo medical treatment.

The total population and area by district from the same year as the survey was conducted were taken from the Statistics of Yogyakarta Municipality (2017), Statistics of Sleman Regency (2017) and Statistics of Bantul Regency (2017). Table 6.3 displays the demographic characteristics across cities/regencies in Yogyakarta Province.

Although our aim is to study the effect of the urban form on transport mode choice, we do not exclude from our sample the households that live in the rural areas of Yogyakarta Province[47]. This leaves us with a sample size of 2,570 and 978 household members for the MNL regression in commuting and leisure activities successively, and 825 household members for the OLR regression, which is equivalent to about 0.15% of the total population size of the area. (Biro Tapem Setda DIY, 2015). Nevertheless, the sample sizes meet the minimum sample size requirement according to Slovin's fromula with 5% margin of error (Ryan, 2013)[48].

We differentiate the residential areas into urban, peri-urban and rural areas. Based on the Statistics of D.I. Yogyakarta Province (2015), we classify urban areas as big and medium cities and peri-urban areas as small cities. The distance from home to public transportation measures the distance from a traveller's home to any public transport stop – like a stop or station for a bus, pedicab, motorcycle taxi, taxi or train. It is to be noted that the number of people who use other forms of public transportation is limited compared with the bus.

The distance from home to a fuel station is the distance from a traveller's home to his/her most frequently used fuel station to obtain gasoline or diesel fuel – it is thus not necessarily the nearest fuel station to their home.[49] To the best of our knowledge, we are the first to use this explanatory variable. The idea here is that a shorter distance to the fuel station might discourage travellers from taking public transportation and encourage them to use private motor vehicles.

In our regression models on transport mode choice that use data on individual household members, income is represented by the average income of household members. In those regression models that use data at the household level, like the models of motor vehicle ownership, income is represented by the household income. The number of children per family is classified into two groups, based on age. The age category of younger children represents the general age of children who have not entered school and children who are in kindergarten (younger than 7 years old), while the category of older children reflects the common age of students in elementary

[47] The urban and peri-urban areas are displayed as dummy variables in the model and the rural area becomes the reference.

[48] Minimum $n_{\text{people}} = \frac{N_{people}}{(1+N_{people} \cdot e^2)} = \frac{2{,}551{,}696}{(1+2{,}551{,}696 \cdot 5\%^2)} = 399.93 \approx 400$ (urban and rural area) and minimum $n_{\text{household}} = \frac{N_{household}}{(1+N_{household} \cdot e^2)} = \frac{623{,}862}{(1+623{,}862 \cdot 5\%^2)} = 399.74 \approx 400$ (urban area only).

[49] Some respondents have difficulties measuring the distance from their home to the nearest fuel station because they usually buy fuel on their way to the location of their commuting activity, which is not the nearest fuel station to their home.

school and junior high school (aged between 7 and 16 years), who are quite capable of going to school independently, that is, without being escorted by their parents. The upper bound of age for older children is the minimum age to obtain a motorcycle driving license in Indonesia.

Table 6.4 – Summary Statistics

Variable		MNL Regression, Activity						OLR		
		Commuting			Leisure					
		N	Mean	St. Dev	N	Mean	St. Dev	N	Mean	St. Dev
AGE	Traveler's age or the average age of household members (year old)	2,510	33.6	17.2	964	34.5	17.7	825	34.6	11.5
EDU	Education attained by traveler or the average of education attained by household members[1)]	2,514	4.4	1.8	967	4.8	2.1	825	4.4	1.4
INCCAP	The average income of household members (International $)[2)]	2,522	336.0	288.5	968	445.7	370.7	825	367.2	351.9
MOCYOWN	Number of motorcycles owned by (traveler's) household	2,522	2.3	1.2	968	2.3	1.2	825	2.1	1.1
CAROWN	Number of cars owned by (traveler's) household	2,522	0.3	0.6	968	0.4	0.7	825	0.2	0.6
BIKEOWN	Number of bicycle owned by (traveler's) household	2,522	0.9	1.2	968	1.0	1.3	825	0.8	1.1
HHSIZE	Number of (traveler's) household members	2,522	4.0	1.4	968	3.8	1.4	825	3.5	1.4
YOUNGCHILD	Number of children < than 7 years old in (traveler's) the household	2,522	0.3	0.5	968	0.3	0.6	825	0.3	0.5
OLDERCHILD	Number of children aged 7 – < 16 y.o. in (traveler's) the household	2,522	0.6	0.8	968	0.6	0.8	825	0.4	0.7
DISDEN	Population density in the district where the (traveler) household lives (people/km^2)	2,522	4,537.6	4,654.0	968	4,995.5	4,779.7	825	5,140.9	4,429.1
CBD	Distance from home to the city center (km)	2,522	10.6	6.6	968	9.8	6.2	825	10.3	6.5
DISTPUB	Distance from home to get a public transportation (m)	2,490	864.3	1,623.1	953	868.3	1,579.7	815	863.8	1,644.5
DISTFUEL	Distance from home to the fuel station (m)	2,514	2,096.3	2,115.5	968	1,891.4	1,679.6	823	2,044.2	2,007.2
DISTCOM	Travel distance (km/trip)	2,505	5.1	6.6				825	5.2	4.7
LDIST					948	13.4	26.9	474	12.5	28.0
FREQCOM	Travel frequency (trip/week)	2,512	4.9	1.2				825	4.9	0.9
LFREQ					962	1.6	1.2	481	1.7	1.3

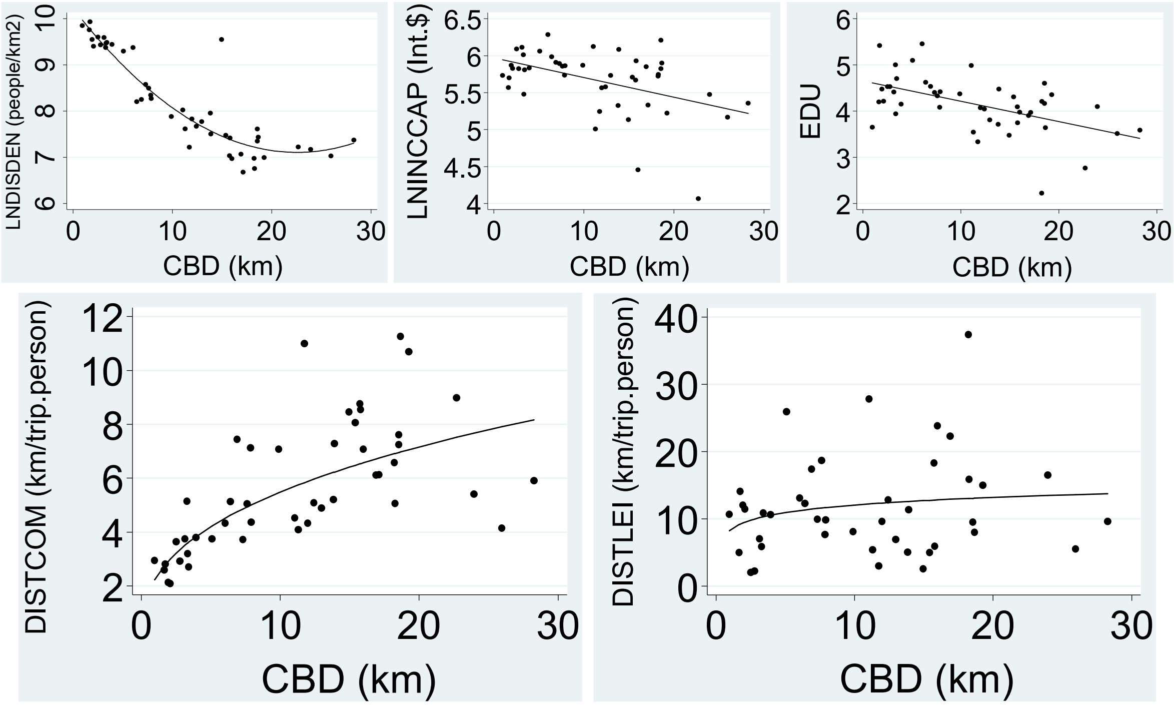
Table 6.4 – Summary Statistics (continued)

	Variable	MNL Regression, Activity				OLR		
		Commuting		Leisure				
		N	%	N	%	N	Mean	St. Dev
FEMALE	Female traveler or percentage of female in the household	2,512	49.1	965	47.8	825	0.5	0.2
WORK	Percentage of household member (traveler) with working activity	2,522	58.8			825	0.2	0.2
STUDY	Percentage of household member (traveler) with study activity	2,522	27.6			825	0.2	0.2
SHOPPING	Percentage of household member (traveler) with shopping activity	2,522	10.5			825	0.1	0.2
						N	%	
URBAN	Household (traveler) who live in urban area[3]	2,517	24.0	965	26.7	823	26.0	
RURAL	Household (traveler) who live in rural area	2,517	8.5	965	8.2	823	9.1	
TRANMODE	Traveler using bus[4]		1.9		2.5			
	Traveler using car		6.6		23.1			
	Traveler using motorcycle[5]	2,522	66.0	968	53.7			
	Traveler who cycling[6]		9.6		2.3			
	Traveler who walking		16.0		18.4			
MOCYOWN	Own no motorcycle						5.8	
	Own 1–2 motorcycles					825	65.0	
	Own 3–4 motorcycles						26.4	
	Own 5–7 motorcycles						2.8	
CAROWN	Own no car						79.9	
	Own 1 car					825	16.6	
	Own 2 cars						2.7	
	Own 3–4 cars						0.9	

Notes: (1) St. Dev = standard deviation. (2) Code for education level: 1 = no schooling, 2 = not completed elementary school, 3 = elementary school, 4 = junior high school, 5 = senior high school, 6 = diploma I/II, 7 = diploma III, 8 = diploma IV/bachelor's degree, 9 = master's/doctoral's degree. (3) Income is converted into international dollar based on the conversion rate from Quandl for 2012 which was retrieved from: https://www.quandl.com/data/ODA/IDN_PPPEX-Indonesia-Implied-PPP-Conversion-Rate-LCU-per-US on December 25, 2015. (4) Urban means villages or sub-districts that are classified into big and medium cities whereas peri-urban refers to villages or sub-districts that are categorized as small cities by Statistics of D.I. Yogyakarta Province (2015). (5) Bus and walking; bus and motorcycle; bus, motorcycle/motorcycle taxi and walking. (6) Only motorcycle; motorcycle and walking. (7) Only bicycle; bicycle and walking. (7) LN = natural logarithm.

Table 6.4 presents the summary statistics of all the variables used in the various regression models. We only consider five types of transport mode, specifically bus, car, motorcycle, bicycle and walking. Other types of transport mode are excluded from the models because their data frequency is very low. We also categorize motorcycle and car ownership into four groups. Table 6.4 shows that motorcycles are the most favoured transport mode.

Figure 6.2 – Cross-District Correlations between the Distance to the CBD and the Traveller's Characteristics



In Figure 6.2, we present the cross-district correlations between the distance to the CBD and, respectively, the population density, income, education, commuting distance and leisure distance for Yogyakarta Province. The figure shows the existence of a negative correlation between the distance from home to the city centre and the per capita income. Hence, people who live near the city centre tend to have a higher income, which also enables them to have a car. Figure 6.2 also shows that people who live farther from the city centre tend to have a longer commuting distance. We can see that the increase in the commuting distance decreases as the distance to the CBD increases. Travel time matters relatively more for commuters with a long travel distance. Obviously, motorcycles are, relative to cars, more suitable for use on congested roads.

Next, we present the correlation between density and travellers' characteristics in Figure 6.3. According to Figure 6.2, the population density has a negative correlation with the distance to the CBD. The scatter plots in Figure 6.3 therefore tend to have opposite relationships between population density and income, education, commuting distance and leisure distance. Hence, people who live in higher-density areas tend to have higher education and therefore a higher income (see also Figure 6.4). People who live in high-density areas are also likely to have a shorter distance for commuting and leisure activities. We can see that the commuting distance decreases in high-density areas. Thus, in Figure 6.4, we can see that people who are highly educated and have high income levels are inclined to have shorter distances for commuting and leisure activities. This indicates that most of the centres for office, school, shopping and entertainment are located around the city centre.

Figure 6.3 – Scatter Plots of the Correlation between Density and Travellers' Characteristics

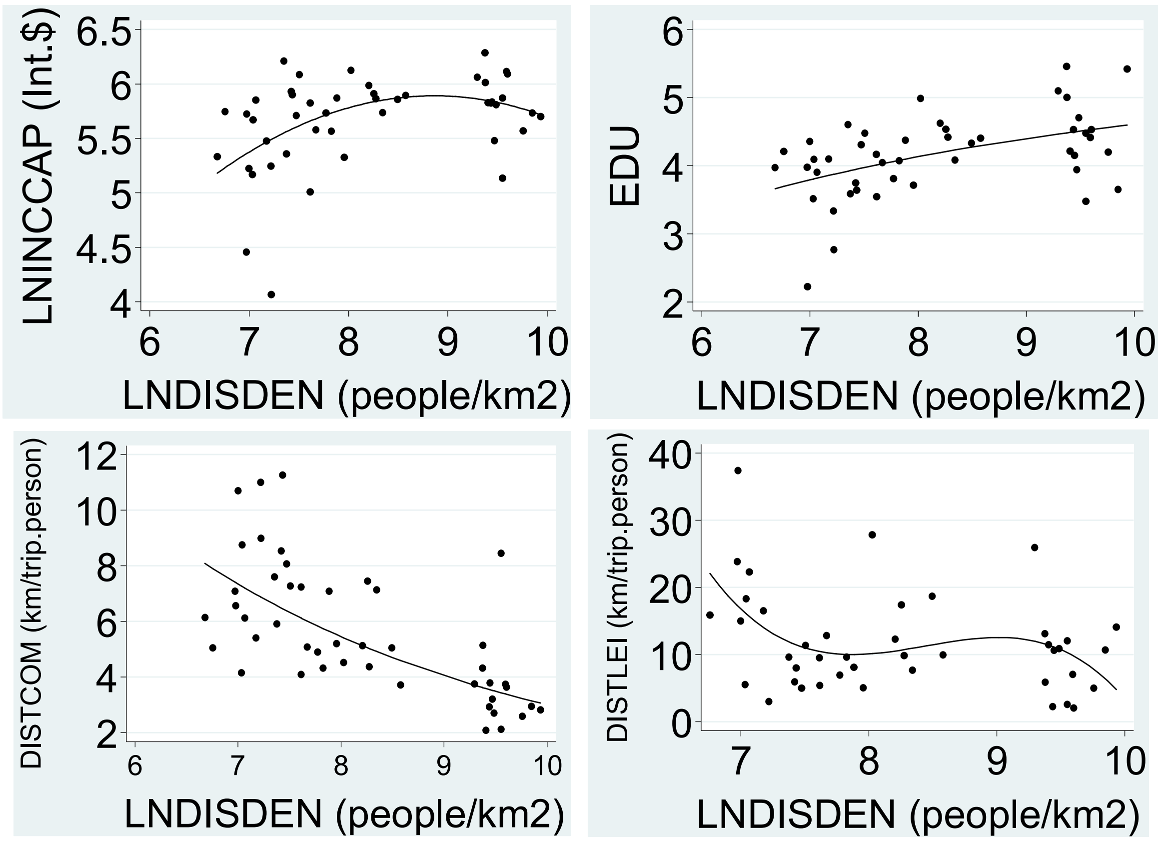


Figure 6.4 – Scatter Plots of the Correlation between Income and Travellers' Characteristics

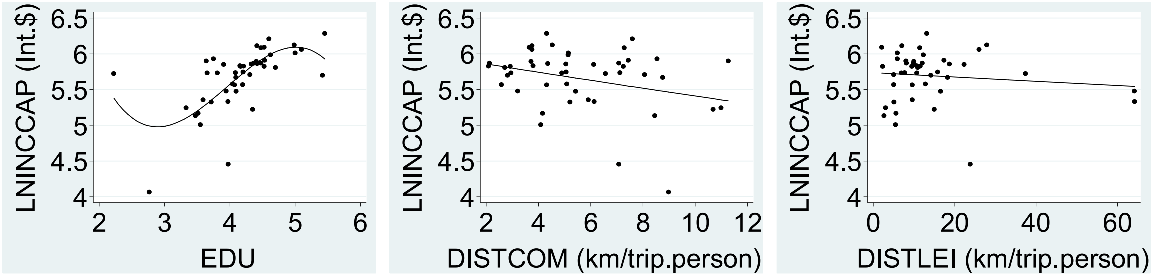


Table 6.5 – Average Travel Distance and Energy Consumption by Transport Mode

	Variable	Car	Bus	Motorcycle	Bicycle	Walk
Commuting	Average travel distance per trip (km/person)	9.4110	6.8705	6.0570	2.8045	0.4324
	Observations	164	48	1,653	241	399
	Very short distance : <1 km	4.2%	6.3%	11.4%	24.9%	85.6%
	Short distance : 1–5 km	42.8%	45.8%	45.6%	62.2%	13.2%
	Medium distance : > 5–≤10 km	22.9%	25.0%	24.5%	7.9%	
	Long distance : > 10–≤20 km	22.3%	20.8%	13.9%	5.0%	
	Very long distance : >20 km	7.8%	2.1%	4.6%		1.2%
	Total distribution	100.0%	100.0%	100.0%	100.0%	100.0%
	Average travel distance per month (km/person)	332.9521	227.6472	241.892	112.2041	17.2804
	Observations	163	48	1,653	241	397
	Total fuel consumption per month (toe)	4.7995	0.3206	18.5046		
	Observations	163	48	1,658		
Leisure	Average travel distance per trip (km/person)	22.9219	36.75	12.6395	11.9257	0.5974
	Observation	219	24	507	22	176
	Very short distance : <1 km	1.3%		11.2%	27.3%	92.1%
	Short distance : 1–5 km	25.4%	16.7%	40.0%	36.4%	5.6%
	Medium distance : > 5–≤10 km	18.3%	16.7%	18.8%	4.5%	
	Long distance : > 10–≤20 km	18.3%	20.8%	13.5%	9.1%	0.6%
	Very long distance : >20 km	36.6%	45.8%	16.5%	22.7%	1.7%
	Total distribution	100.0%	100.0%	100.0%	100.0%	100.0%
	Average travel distance per month (km/person)	206.9733	367.0000	151.1937	136.2691	10.6310
	Observations	217	24	507	22	176
	Total fuel consumption per month (toe)	3.1737	0.1851	1.8753		
	Observations	217	19	507		

To have a better understanding of the effect of travel distance on transport mode choice, Table 6.5 shows the travel distance and fuel consumption by type of activity and transport mode. We can see that people who travel by bicycle, bus and motor vehicle tend to have a longer travel distance for leisure activity than for commuting activity. For commuting and leisure activities, walking is likely to be chosen for a very short travel distance, that is, less than 1 kilometre. For commuting activity, on average cycling is used for a short distance, whereas motorcycles, buses and cars are used for a medium distance, that is, in the range of 5 to 10 kilometres. For leisure activity, on average, motorcycles and bicycles are used for long distances, that is, between 10 and 20 kilometres, and buses and cars are used for very long travel distances exceeding 20 kilometres.

Finally, Table 6.6 displays the travel distance from previous studies. The average travel distance of walking in Yogyakarta Province is shorter than that in other countries, which might be because of the hot and humid weather conditions in Yogyakarta Province. Table 6.6 also shows that, although motorcycles consume less fuel than cars, the total fuel consumption of motorcycles is higher than that of cars: the motorcycle is the favoured transport mode. About 66% of commuters and 54% of travellers for leisure activity are motorcycle users (see Table 6.4).

Table 6.6 – Travel Distance by Transport Mode from Previous Studies

	Distance (km)		Location	Source
	Average	With Highest %		
Walk	0.8–0.9		Netherlands	Dieleman et al. (2002)
	0.71–0.859		Germany	Muller (2008)
	1.17		China	Sun et al. (2017)
		≤ 0.8	Germany	Scheiner (2010)
Cycling	2.7–4.8		Netherlands	Dieleman et al. (2002)
	2.022–2.364		Germany	Muller (2008)
	4.62		China	Sun et al. (2017)
Public Transportation	2.5–7.1		Netherlands	Dieleman et al. (2002)
	4.943–5.390		Germany	Muller (2008)
	11.72		China	Sun et al. (2017)
Car/Motorcycle	14.4–24.3		Netherlands	Dieleman et al. (2002)
	6.036–7.693		Germany	Muller (2008)
	±11		United Kingdom	Clark et al. (2016)
	8.99		China	Sun et al. (2017)
		<4.8	Germany, United States	Buehler (2011)
		>0.8	Germany	Scheiner (2010)

6.5 Regression Results

In section 6.5.1, we present the results for the regression models of transport mode choice. In section 6.5.2, we present the results for the regression models of motorcycle and car ownership. Throughout all the analyses, the explanatory variables in Model A consist only of travellers' personal and household characteristics, whereas Model B includes travel characteristics and some indicators of urban form. Taking Muniz and Galindo's (2005) suggestion, we include the population density and the distance from home to the city centre in separate models, because there is a strong correlation between the two variables. The results of those models are similar. Because the population density and the distance between the home and the city centre are negatively correlated, most of the effects of the two variables are in the opposite direction.

6.5.1 Transport Mode Choice

Table 6.7 – RRR of the MNL Regression for Commuting Activity

Explanatory Variables	Model A1				Model A2			
	TRANMODE (Reference: MOTORCYCLE)				TRANMODE (Reference: MOTORCYCLE)			
	BUS	CAR	BICYCLE	WALK	BUS	CAR	BICYCLE	WALK
FEMALE	3.543***	0.586**	1.048	2.130***	3.617***	0.563**	1.046	2.159***
AGE	1.039***	1.031***	1.006	1.038***	1.038***	1.035***	1.006	1.037***
EDU	0.753***	1.145**	0.521***	0.697***	0.753**	1.064	0.519 ***	0.714***
LNINCCAP					1.401*	2.159***	1.043	0.952
HHSIZE					1.758***	1.179	1.188 **	1.351***
YOUNGCHILD	1.075	0.954	0.533***	1.339***	0.681	1.021	0.458 ***	0.981
OLDERCHILD	1.011	1.799***	1.122	1.197*	0.760	1.855***	1.012	0.967
MOCYOWN	0.502***	0.567***	0.618***	0.692***	0.357***	0.541***	0.564 ***	0.591***
CAROWN	0.972	8.288***	0.614**	0.876	0.795	5.913***	0.624 *	0.920
BIKEOWN	1.061	0.981	0.614***	0.923	0.986	1.015	1.986 ***	0.883*
CONSTANT	0.043***	0.014***	1.731*	0.395***	0.002***	0.000***	0.994	0.266**
Wald Chi²	792.2591 ***				840.1792 ***			
Pseudo R²	0.23				0.24			
N	2,502				2,502			

Explanatory Variables	Model B1				Model B2			
	TRANMODE (Reference: MOTORCYCLE)				TRANMODE (Reference: MOTORCYCLE)			
	BUS	CAR	BICYCLE	WALK	BUS	CAR	BICYCLE	WALK
FEMALE	3.139***	0.531**	0.832	1.422**	3.158***	0.535**	0.839	1.442**
AGE	1.054***	1.028**	1.056***	1.030***	1.054***	1.027***	1.056***	1.031***
EDU	0.765***	1.005	0.651***	0.792***	0.771**	1.023	0.654***	0.800***
LNINCCAP	1.379	1.902***	1.130	1.055	1.430*	1.969***	1.161	1.070
HHSIZE	1.830***	1.205	1.289**	1.318***	1.844***	1.228*	1.311***	1.333***
YOUNGCHILD	0.579	0.977	0.448***	0.735*	0.577	0.923	0.445***	0.726**
OLDERCHILD	0.736	2.006***	0.925	0.941	0.725	2.041***	0.892	0.921
MOCYOWN	0.309***	0.524***	0.532***	0.670***	0.305***	0.525***	0.526***	0.655***
CAROWN	0.517	6.799***	0.590**	1.021	0.515	6.698***	0.588**	1.014
BIKEOWN	1.062	1.007	2.041***	0.905	1.063	0.964	2.062***	0.910
CBD	1.004	0.933**	1.029*	1.010				
LNDENSITY					0.743	1.073	0.638***	0.769**
URBAN	0.828	0.675	0.757	1.123	0.893	0.825	0.788	1.187
RURAL	0.585	0.892	1.374	1.610*	0.491	0.724	1.196	1.388
DISTPUB	0.999**	1.000**	1.000	1.000	0.999**	1.000**	1.000	1.000
DISTFUEL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DISTCOM	1.063***	1.041***	0.870***	0.159***	1.058***	1.036***	0.865***	0.160***
FREQCOM	0.775**	0.750***	1.044	0.933	0.779***	0.745***	1.056	0.943
WORK	0.737	0.669	3.321	1.715	0.769	0.660	3.580	1.809
STUDY	3.267	0.362	40.154***	2.202	3.512	0.368	44.661***	2.463
SHOPPING	1.264	0.371*	6.452*	3.017**	1.273	0.370*	7.013*	3.181**
CONSTANT	0.004***	0.004***	0.006***	0.823	0.038**	0.001***	0.217	6.065
Wald Chi²	849.2965 ***				816.5343 ***			
Pseudo R²	0.42				0.42			
N	2,440				2,440			

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at the 10%, 5% and 1% level.

As described in section 6.3, to identify the role of the urban form in preferences for the use of motorcycles, we employ a multinomial logistic (MNL) regression model, and we present the results of this MNL regression approach in terms of the relative risk ratio (*RRR*) and the marginal effects.

Table 6.8 – RRR of the MNL Regression for Leisure Activity

Explanatory Variables	Model A3				Model A4			
	TRANMODE (Reference: MOTORCYCLE)				TRANMODE (Reference: MOTORCYCLE)			
	BUS	CAR	BICYCLE	WALK	BUS	CAR	BICYCLE	WALK
FEMALE	1.817	0.901	0.625	2.565***	1.844	0.923	0.680	2.689***
AGE	1.017	1.008	1.032**	1.043***	1.017	1.013	1.033**	1.042***
EDU	0.965	1.091	0.812	0.735***	0.902	1.055	0.831	0.780***
LNINCCAP					1.885*	1.466*	0.728	0.559***
HHSIZE					1.028	0.847	0.687*	0.937
YOUNG CHILD	1.334	3.933***	1.154	1.313	1.717	4.983***	1.457	1.168
OLDER CHILD	1.090	3.092***	1.219	1.776***	1.253	3.786***	1.348	1.547***
MOCY OWN	0.328***	0.479***	0.690*	0.773***	0.308***	0.542***	0.860	0.858
CAROWN	2.478	63.917***	1.398	1.562	1.755	55.486***	1.628	2.133**
BIKEOWN	0.550*	1.227	1.689***	1.015	0.598*	1.268	1.813***	1.017
CONSTANT	0.163*	0.018***	0.039***	0.187***	0.005**	0.002***	0.365	3.841
Wald Chi^2	310.7280 ***				353.3426 ***			
Pseudo R^2	0.35				0.37			
N	962				962			
Explanatory Variables	**Model B3**				**Model B4**			
	TRANMODE (Reference: MOTORCYCLE)				**TRANMODE (Reference: MOTORCYCLE)**			
	BUS	**CAR**	**BICYCLE**	**WALK**	**BUS**	**CAR**	**BICYCLE**	**WALK**
FEMALE	2.216*	0.803	0.605	2.153***	2.270*	0.804	0.627	2.188***
AGE	1.012	1.010	1.027*	1.029***	1.013	1.009	1.026	1.029***
EDU	0.867	1.172**	0.825	0.903	0.861	1.179**	0.828	0.903
LNINCCAP	2.067*	1.292	0.672	0.619***	2.049*	1.297	0.667	0.631***
HHSIZE	1.125	0.727*	0.652*	0.839	1.129	0.726*	0.676*	0.851
YOUNG CHILD	1.803	4.445***	1.793	1.279	1.971	4.435***	1.860	1.325
OLDER CHILD	0.637	4.515***	1.320	1.584***	0.571	4.664***	1.232	1.612***
MOCY OWN	0.279***	0.560***	0.936	0.877	0.283***	0.566***	0.927	0.863
CAROWN	1.936	81.042***	2.124	2.086*	1.732	83.808***	2.058	2.070*
BIKEOWN	0.637	1.202	1.898***	1.034	0.640	1.177	1.866***	1.009
CBD	1.068	0.974	1.030	0.979				
LN DENSITY					0.483**	1.160	0.520	0.919
URBAN	0.884	0.506*	1.781	1.014	0.948	0.531*	2.173	1.144
RURAL	0.366	0.284**	4.706**	1.113	0.386	0.290*	3.718*	0.959
DISTPUB	1.000	1.000	1.000***	1.000	1.000	1.000	1.000***	1.000
DISTFUEL	1.000	1.000	1.000***	1.000	1.000	1.000	0.999***	1.000
DISTLEI	1.037***	1.029***	0.991	0.403*	1.036***	1.029***	0.992	0.406*
FREQLEI	1.089	0.420***	1.261	1.089	1.103	0.416***	1.263	1.100
CONSTANT	0.002**	0.016**	0.406	14.146**	1.532	0.004*	112.287	21.181*
Wald Chi^2	374.6929 ***				381.3410 ***			
Pseudo R^2	0.52				0.52			
N	921				921			

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at the 10%, 5% and 1% level.

In Tables 6.7 and 6.8, we present the relative risk ratio (*RRR*) of the preferences for using motorcycles for, respectively, commuting and leisure activities. Tables 6.9 and 6.10 contain the marginal effects for using motorcycles in, respectively, commuting and leisure activities.

Table 6.9 – Marginal Effect of the MNL Regression for Commuting Act

Explanatory Variables	Model A5					Model A6				
	BUS	CAR	MOTORCYCLE	BICYCLE	WALK	BUS	CAR	MOTORCYCLE	BICYCLE	WALK
FEMALE	0.0195***	−0.0264***	−0.0674***	−0.0103	0.0846***	0.0195***	−0.0276***	−0.0662***	−0.0106	0.0849***
AGE	0.0005***	0.0010***	−0.0050***	−0.0003	0.0039***	0.0004**	0.0011***	−0.0049***	−0.0003	0.0037***
EDU	−0.0020	0.0090***	0.0629***	−0.0385***	0.0314***	−0.0020	0.0059***	0.0626***	−0.0388***	−0.0277***
LNINCCAP						0.0057*	0.0300***	−0.0245**	0.0012	−0.0124
HHSIZE						0.0081**	0.0040	−0.0459***	0.0054*	0.0284***
YOUNGCHILD	0.0011	−0.0021	0.0043	−0.0476***	0.0443***	−0.0053	0.0030	0.0421**	−0.0521***	0.0123
OLDERCHILD	−0.0014	0.0221***	−0.0404***	0.0036	0.0161	−0.0053	0.0245***	−0.0139	0.0005	−0.0058
MOCYOWN	−0.0093***	−0.0189***	0.0814***	−0.0243***	−0.0289***	−0.0142***	−0.0191***	0.1037***	−0.0270***	−0.0433***
CAROWN	−0.0003	0.0859***	−0.0303	−0.0359**	−0.0193	−0.0041	0.0711***	−0.0225	−0.0343**	−0.0102
BIKEOWN	4.5e-5	−0.0020	−0.0266***	0.0494***	−0.0209***	−0.0010	−0.0003	−0.0219***	0.0487***	−0.0255***
Explanatory Variables	**Model B5**					**Model B6**				
	BUS	**CAR**	**MOTORCYCLE**	**BICYCLE**	**WALK**	**BUS**	**CAR**	**MOTORCYCLE**	**BICYCLE**	**WALK**
FEMALE	0.0193***	−0.0244***	−0.0040	−0.0178*	0.0268**	0.0193***	−0.0243***	−0.0051	−0.0175*	0.0277**
AGE	0.0006***	0.0008**	−0.0055***	0.0028***	0.0012**	0.0006***	0.0007*	−0.0055***	0.0028***	0.0013***
EDU	−0.0029	0.0018	0.0349***	−0.0233***	−0.0104**	−0.0028	0.0024	0.0332***	−0.0230***	−0.0098**
LNINCCAP	0.0043	0.0224***	−0.0316***	0.0050	−0.0001	0.0048	0.0237***	−0.0352***	0.0064	0.0003
HHSIZE	0.0087***	0.0049	−0.0388***	0.0105*	0.0146***	0.0087**	0.0056	−0.0407***	0.0112*	0.0151***
YOUNGCHILD	−0.0065	0.0020	0.0598***	−0.0452***	−0.0100	−0.0064	−0.0001	0.0620***	−0.0449***	−0.0106
OLDERCHILD	−0.0055	0.0256***	−0.0111	−0.0047	−0.0043	−0.0056	0.0265***	−0.0090	−0.0066	−0.0054
MOCYOWN	−0.0166***	−0.0199***	0.0829***	−0.0304***	−0.0161**	−0.0167***	−0.0199***	0.0845***	−0.0305***	−0.0174***
CAROWN	−0.0117	0.0704***	−0.0286	−0.0355**	0.0054	−0.0117	0.0704***	−0.0283	−0.0355**	0.0050
BIKEOWN	−0.0004	−0.0009	−0.0278***	0.0462***	−0.0170***	−0.0004	−0.0025	−0.0269***	0.0466***	−0.0168***
CBD	3.9e-5	−0.0026**	0.0003	0.0018**	0.0005					
LNDENSITY						−0.0033	0.0043	0.0354***	−0.0240**	−0.0123
URBAN	−0.0024	−0.0137	0.0205	−0.0180	0.0136	−0.0015	−0.0068	0.0087	−0.0167	0.0163
RURAL	−0.0107	−0.0054	−0.0307	0.0150	0.0317	−0.0127	−0.0122	−0.0078	0.0090	0.0236
DISTPUB	−1.0e-5 *	6.0e-6 ***	9.8e-7	2.7e-6	3.1e-6	−1.0e-5 *	5.5e-6 **	2.7e-6	1.9e-6	2.0e-6
DISTFUEL	5.5e-7	4.2e-7	−1.8e-7	6.2e-9	8.2e-7	3.9e-7	−2.5e-6 *	5.1e-6	1.2e-6	4.1e-7
DISTCOM	0.0056***	0.0062***	0.1034***	0.0159***	−0.1310***	0.0055***	0.0061***	0.1032***	0.0157***	−0.1304***
FREQCOM	−0.0039**	−0.0100***	0.0134*	0.0048	−0.0043	−0.0039**	−0.0103***	0.0125*	0.0053*	−0.0037
WORK	−0.0087	−0.0177	−0.0678	0.0698	0.0244	−0.0083	−0.0186	−0.0732	0.0732	0.0270
STUDY	0.0104	−0.0464**	−0.1919***	0.2211***	0.0068	0.0109	−0.0466**	−0.2017***	0.2246***	0.0128
SHOPPING	−0.0020	−0.0420**	−0.1163*	0.1038	0.0565	−0.0023	−0.0427***	−0.1214**	0.1075	0.0588

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** – significant at 10%, 5% and 1% level.

Table 6.10 – Marginal Effect of the MNL Regression for Leisure Activity

Explanatory Variables	Model A7					Model A8				
	BUS	CAR	MOTORCYCLE	BICYCLE	WALKING	BUS	CAR	MOTORCYCLE	BICYCLE	WALK
FEMALE	0.0083	−0.0229	−0.0870***	−0.0153	0.1170***	0.0090	−0.0210	−0.0919***	−0.0138	0.1178***
AGE	0.0001	−0.0003	−0.0051***	0.0004	0.0048***	0.0001	0.0001	−0.0050***	0.0004	0.0044***
EDU	0.0008	0.0111**	0.0290***	−0.0030	−0.0380***	−0.0011	0.0078*	0.0248***	−0.0027	−0.0288***
LNINCCAP						0.0154**	0.0311**	0.0342*	−0.0047	−0.0760***
HHSIZE						0.0017	−0.0089	0.0180	−0.0074*	−0.0034
YOUNGCHILD	−0.0002	0.0836***	−0.0916***	−0.0013	0.0092	0.0050	0.0968***	−0.0958***	0.0037	−0.0097
OLDERCHILD	−0.0053	0.0636***	−0.1084***	−0.0012	0.0512***	−0.0022	0.0766***	−0.1052***	0.0012	0.0296*
MOCYOWN	−0.0207***	−0.0393***	0.0759***	−0.0046	−0.0113	−0.0226***	−0.0320***	0.0578***	−0.0006	−0.0027
CAROWN	0.0036	0.2599***	−0.2406***	−0.0041	−0.0187	−0.0063	0.2406***	−0.2578***	0.0022	0.0257
BIKEOWN	−0.0143*	0.0140*	−0.0100	0.0111***	−0.0008	−0.0124*	0.0154**	−0.0133	0.0125***	−0.0022

Explanatory Variables	Model B7					Model B8				
	BUS	CAR	MOTORCYCLE	BICYCLE	WALKING	BUS	CAR	MOTORCYCLE	BICYCLE	WALK
FEMALE	0.0141	−0.0188	−0.0451*	−0.0132	0.0630***	0.0143	−0.0190	−0.0470*	−0.0126	0.0642***
AGE	0.0001	0.0002	−0.0028***	0.0004	0.0021**	0.0001	0.0002	−0.0028***	0.0004	0.0021***
EDU	−0.0029	0.0098**	0.0052	−0.0038	−0.0083	−0.0030	0.0101**	0.0049	−0.0037	−0.0083
LNINCCAP	0.0139*	0.0150	0.0186	−0.0073	−0.0403***	0.0136*	0.0152	0.0176	−0.0075	−0.0388***
HHSIZE	0.0038	−0.0150*	0.0293**	−0.0077	−0.0104	0.0039	−0.0153*	0.0279**	−0.0070	−0.0095
YOUNGCHILD	0.0052	0.0728***	−0.0918***	0.0084	0.0054	0.0066	0.0723***	−0.0957***	0.0089	0.0080
OLDERCHILD	−0.0147	0.0762***	−0.0890***	0.0017	0.0258**	−0.0168	0.0784***	−0.0894***	0.0001	0.0276**
MOCYOWN	−0.0216***	−0.0248*	0.0489***	0.0007	−0.0032	−0.0210***	−0.0243**	0.0492***	0.0005	−0.0045
CAROWN	−0.0045	0.2199***	−0.2430***	0.0051	0.0226	−0.0069	0.2226***	−0.2423***	0.0043	0.0223
BIKEOWN	−0.0094	0.0098*	−0.0134	0.0131***	−1.3e-5	−0.0091	0.0089	−0.0108	0.0128***	−0.0017
CBD	0.0013	−0.0015	0.0012	0.0007	−0.0018					
LNDENSITY						−0.0135**	0.0119	0.0185	−0.0132	−0.0038
URBAN	−0.0003	−0.0362*	0.0191	0.0132	0.0042	0.0005	−0.0352*	0.0053	0.0167	0.0126
RURAL	−0.0154	−0.0657**	0.0324	0.0345**	0.0142	−0.0139	−0.0633*	0.0443	0.0299*	0.0029
DISTPUB	−5.6e-6	−3.0e-7	−1.0e-5	4.8e-6 **	1.1e-5	−7.1e-6	2.6e-5	−8.2e-6	4.4e-6 **	1.1e-6
DISTFUEL	−4.5e-6	−2.2e-6	1.3e-5	−1.1e-5 ***	4.0e-6	−5.0e-6	2.8e-6	1.8e-6 *	−1.1e-5 ***	3.9e-7
DISTLEI	0.0026**	0.0080***	0.0593**	0.0031**	−0.0730**	0.0026**	0.0079**	0.0589**	0.0031**	−0.0725**
FREQLEI	0.0042	−0.0464***	0.0241**	0.0060*	0.0121	0.0045	−0.0472***	0.0238**	0.0060*	0.0129*

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at 10%, 5% and 1% level.

In Tables 6.7 and 6.8, the pseudo R^2 shows that travellers' personal and household characteristics can explain, respectively, about 24% and 37% of the variance in transport mode choice for commuting and leisure activities. Including travel characteristics and the urban form increases the pseudo R^2 in the models for commuting and leisure activities to 42% and 52%, respectively. Hence, the urban form and travel characteristics contribute substantially to explaining transport mode preferences. We continue by describing in detail the role of the urban form and travel characteristics in determining transport mode choice. We refer to Appendix B.1 for a detailed description of how travellers' personal and household characteristics affect their transport mode choice for commuting and leisure activities.

Urban Form and Travel Characteristics

The average distances between the city centre and the home in urban areas, peri-urban areas and rural areas are, respectively, 5.5 km, 11.3 km and 17.3 km. Compared with those who live in a peri-urban area, commuters who live in a rural area have a higher tendency to walk than to use a motorcycle (see Model B1 in Table 6.7). We find that, for commuting activity, the distance between home and the city centre decreases the probability of using a car and increases the probability of using a bicycle relative to the probability of using a motorcycle (see Model B1 in Table 6.7). In other words, people who live near the city centre have a higher likelihood of travelling by car than by motorcycle and people who live far from the city centre have a higher tendency to travel by bicycle than by motorcycle. However, the effect is not big. An increase of 1 kilometre in the distance between the house and the city centre reduces the probability of a commuter driving a car by 0.26% and increases the probability of commuting by cycling by 0.18% (see Model B5 in Table 6.9). For leisure activity, the distance between the home and the city centre has an insignificant effect on the transport mode preference (Model B3 in Table 6.8 and Model B7 in Table 6.10).

We find that, for commuting activity, the urban or rural character of areas has no statistically significant effect on the transport mode preference (see Tables 6.7 and 6.9). For leisure activity, however, we find that, in comparison with people who live in peri-urban areas, people who live in urban and rural areas have a lower likelihood of using a car relative to a motorcycle (see Models B3–B4 in Table 6.8). More precisely, compared with people who live in peri-urban areas, travellers who live in urban and rural areas have, respectively, a 3.5%–3.6% and 6.3%–6.6% lower probability of driving a car (see Models B7–B8 in Table 6.10). Travellers who live in a rural area have a 3.0%–3.5% higher probability of cycling relative to those who live in an urban area (see Models B7–B8 in Table 6.10).[50]

For commuting activity, the population density has a significant negative effect on the likelihood of cycling and walking compared with using a motorcycle (see Model B2 in Table 6.7). A 1% decrease in the population density decreases the tendency to use a motorcycle by 0.035% and increases the probability of cycling by 0.024% (see Model B6 in Table 6.9). People who live in a less dense area tend to have a lower income – our data show a positive correlation between population density and per capita income (see Figure 6.3 and Table 6.16 in the Appendix). Therefore, people who choose using the car over the motorcycle are people with higher income who tend to live around the CBD. People who choose to ride a bike over motorcycle are those with relatively low incomes who tend to live far from the CBD. It is to be noted that is also more comfortable to cycle and walk in a low-density area (far from the CBD) with less motor vehicle than in a high-density area (close to the CBD). For leisure activity, the population density has a negative significant effect on the probability of using a bus as compared with a motorcycle (see Model B4 in Table 6.8). A 1% denser area reduces travellers' interest in taking the bus by 0.0135% (see Model B8 in Table 6.10).

The distance from travellers' home to a public transport stop influences their transport mode preferences. In our sample, the average distance from home to a public transport stop for urban, peri-urban and rural areas is, respectively, about 364 metres, 1 kilometre and 1.3 kilometres. Thus, access to public transport is easier in urban areas than in peri-urban and rural areas. Although the distance to a public transport stop is not very far even in peri-urban areas, the hot climate is likely to influence negatively people's willingness to walk this far to access public transport. We find that, for commuting activity, the distance from home to a public transport stop has a significant negative impact on the tendency to use the bus and a positive

[50] These results are similar to the findings in Europe. In the Netherlands, Dieleman et al. (2002) and Limtanakool et al. (2006) found that people who live in a suburb or a less urbanized area tend to travel by car, but they compared cars with public transportation. In the United Kingdom, Clarck et al. (2016) discovered that people who live in a rural area have a higher likelihood of cycling or walking than those who live in inner or outer London. However, our study does not support their finding that people who live in inner or outer London have a lower probability of using a car than those who live in a rural area.

significant effect on the probability of using car as compared with a motorcycle (see Models B1–B2 in Table 6.7). An increase in the distance from home to a public transport stop of 1 metre decreases the probability of using the bus by 0.001% and raises the probability of using a car by about 0.0006% (see Models B5–B6 in Table 6.9). Furthermore, for leisure activity, we find that the distance between the home and the public transport stop increases the probability of riding a bicycle compared with a motorcycle (see Models B5–B6 in Table 6.8). An increase of 1 metre in the distance from home to a public transport stop increases the probability of cycling by 0.0004%–0.0005% (see Models B7–B8 in Table 6.10).

The distance from home to the fuel station does not affect commuters' transport mode choice. For leisure activity, a longer distance between the home and the fuel station decreases the chance of riding a bicycle rather than a motorcycle (see Models B3–B4 in Table 6.8 and Models B7–B8 in Table 6.10). Thus, for leisure activity, a longer distance between the home and the fuel station does not discourage travellers from using a private motor vehicle, which probably can be explained by the fact that, for leisure activity, people tend to travel further, and it is more convenient to travel by private motor vehicle than by public transport or non-motorized transport mode, especially if the distance is long.

We find that, for both commuting and leisure activities, the travel distance significantly increases the possibility of travelling by bus and car, motorcycle and bicycle and reduces the likelihood of walking. For commuting activity, a 1 kilometre longer travel distance increases the probability of travelling by bus, car, motorcycle and bicycle, respectively, by about 0.56%, 0.62%, 10.34% and 1.6% and reduces the possibility of walking by about 13% (see Models B6–B5 in Table 6.9). For leisure activity, an increase in the travel distance by 1 kilometre increases the probability of travelling by bus, car, motorcycle and bicycle, respectively, by about 0.3%, 0.8%, 5.9% and 0.3% and reduces the possibility of walking by about 7.3% (see Models B7–B8 in Table 6.10). However, when compared with using a motorcycle, a longer travel distance increases the likelihood of taking a bus or a car and decreases the chance of walking (see Models B1–B2 in Table 6.7 and Models B3–B4 in Table 6.8). For commuting activity, the travel distance also has a negative significant effect on the probability of using a bicycle relative to a motorcycle (see Models B1–B2 in Table 6.7).[51]

Furthermore, we find for both commuting and leisure activities that the travel frequency reduces the likelihood of travelling by car compared with travelling by motorcycle (see Models B1–B2 in Table 6.7 and Models B3–B4 in Table 6.8). For commuting activity, the travel frequency also decreases the tendency to travel by bus compared with a motorcycle (see Models B1–B2 in Table 6.7). For commuting activity, an increase of 1 trip per week increases the probability of using a motorcycle by 1.25%–1.34% and decreases the chance of choosing a bus and car, respectively, by about 0.4% and 1.0% (see Models B5–B6 in Table 6.9). For leisure activity, the effect of the travel frequency on the tendency to use a motorcycle or a bicycle or to walk is positive. An increase of 1 trip per week increases the probability of riding a motorcycle, cycling or walking, respectively, by about 2.4%, 0.6% and 1.21%–1.29% and reduces the likelihood of choosing a car by about 4.6%–4.7% (see Models B7–B8 in Table 6.10). The relatively lower chance of travelling by bus in comparison with a motorcycle when the travel frequency is high might be caused by the fact that motorcycle use is mostly cheaper than travelling by bus.

Among the urban form factors that have a substantial influence on the preference for motor vehicles in commuting activity are the population density and the distance to the CBD. Among the travel characteristics, the factors that have a strong influence on the preference for motor vehicles for commuting activity are the commuting distance and study activity.

[51] These results reinforce the findings of Muller (2008), Irawan and Sumi (2011a), Heinen et al. (2013), Clark et al. (2016) and Marquet and Miralles-Guasch (2016). Yagi et al. (2014) found that travel distance for work activity has a positive significant effect on the preference to use a car and public transportation in Jakarta. For study activity, however, they discovered that travel distance has a positive significant effect on the use of a car and a negative significant effect on the use of public transportation. Our finding on the effect of travel distance on transport mode choice explains why in our prior study there is a positive significant correlation between the average commuting distance of household members and the per capita energy expenditure on transport (Fevriera & Mulder, 2017).

6.5.2 Ownership of Motorcycles and Cars

As described in section 6.3, to identify the input of urban form to preferences for the ownership of motorcycles and cars, we employ an ordinal logit regression (OLR) model. In this section, we present the results of this OLR approach in terms of the odds ratio (Tables 6.11 and 6.12) and the marginal effects (Tables 6.13 and 6.14). In the models of household ownership of private motor vehicles, the travel characteristics of leisure activity are excluded,[52] but they are included in Models B11–B12 in Table 6.11, Models B15–B16 in Table 6.12, Models B19–B20 in Table 6.13 and Models B23–B24 in Table 6.14.

Table 6.11 – Odds Ratio of the OLR on Motorcycle Ownership

Explanatory Variables	Model A9	Model A10	Model B9	Model B10	Model B11	Model B12
FEMALE	0.5995	0.5037*	0.4781*	0.4865*	0.3689*	0.3702*
AGE	0.9601***	0.9450***	0.9519***	0.9522***	0.9687**	0.9689**
EDU	1.2180***	1.1598*	1.2141**	1.2169**	1.2970**	1.2947**
LNINCCAP		1.6669***	1.6903***	1.7020***	1.4246*	1.4317*
HHSIZE		4.0926***	4.2630***	4.2731***	3.9261***	3.9338***
YOUNGCHILD	0.7393	0.2028***	0.2497***	0.2495***	0.3074***	0.3079***
OLDERCHILD	0.9393	0.3367***	0.3513***	0.3476***	0.4568***	0.4522***
CAROWN	1.4347**	1.1732	1.1243	1.1195	1.0721	1.0667
BIKEOWN	1.1845**	0.9905	0.9457	0.9462	1.0628	1.0651
CBD			1.0096		1.0101	
LNDENSITY				0.8737		0.9226
URBAN			0.7529	0.7787	0.9664	0.9580
RURAL			0.8881	0.8489	0.6296	0.6267
DISTPUB			1.0001	1.0000	1.0001	1.0001
DISTFUEL			1.0000	1.0000	1.0000	1.0000
DISTLEI					0.9980	0.9979
FREQLEI					1.0095	1.0077
DISTCOM			1.0112	1.0093	1.0196	1.0192
FREQCOM			0.9048	0.9096	1.0238	1.0280
WORK			4.4640***	4.5039***	5.2350**	5.2260**
STUDY			4.1510**	4.3200**	4.0039*	4.0708*
SHOPPING			3.0806*	3.0966*	3.6351	3.6583
CUT1	−3.6202	1.3590	2.9264	1.8170	3.5034	2.7941
CUT2	0.2839	6.4809	8.1621	7.0553	8.6594	7.9504
CUT3	3.0211	10.1435	11.8804	10.7802	12.5497	11.8456
Wald Chi^2	51.3935***	256.0565***	259.4965***	259.4621***	157.2557***	157.1912***
Pseudo R^2	0.0424	0.2511	0.2649	0.2654	0.2626	0.2626
N	825	825	812	812	463	463

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at the 10%, 5% and 1% level.

In the models of household ownership of private motor vehicles, travellers' personal and household characteristics explain, respectively, about 25% of the variance in households' motorcycle ownership and 27% of the variance in households' car

[52] See Models B9–B10 in Table 6.11, Models B13–B14 in Table 6.12, Models B17–B18 in Table 6.13 and Models B21–B22 in Table 6.14.

ownership successively (see Model A10 in Table 6.11 and Model A12 in Table 6.12). Adding the travel characteristics and urban form increases the R^2 of the model for household ownership of motorcycles and cars by less than 3%. Thus, the urban form and travel characteristics make a substantial contribution to the transport mode preference, while travellers' personal and household characteristics have a dominant influence on the household ownership of motor vehicles.

Table 6.12 – Odds Ratio of the OLR on Car Ownership

Explanatory Variables	Model A11	Model A12	Model B13	Model B14	Model B15	Model B16
FEMALE	1.0180	0.9643	0.8440	0.8502	0.8149	0.8171
AGE	1.0001	1.0002	1.0150	1.0154	1.0092	1.0118
EDU	2.6832***	1.8560***	1.9803***	1.9780***	1.9794***	1.9849***
LNINCCAP		4.8606***	4.4940***	4.5001***	6.7544***	6.7656***
HHSIZE		1.3736**	1.3535**	1.3564**	1.5886**	1.5937**
YOUNGCHILD	2.2624***	1.9865**	2.2301***	2.2215***	2.1078*	2.1224*
OLDERCHILD	2.7575***	2.5076***	2.0847***	2.0604***	2.5559***	2.4945***
MOCYOWN	1.3419***	1.1747	1.1697	1.1673	1.1631	1.1633
BIKEOWN	1.0079	1.0237	1.0396	1.0438	0.9270	0.9303
CBD			1.0107		1.0158	
LNDENSITY				0.8991		0.7928
URBAN			1.0351	1.0477	1.0633	1.1287
RURAL			0.4642*	0.4538*	0.4386	0.4225
DISTPUB			1.0001	1.0001	1.0000	1.0000
DISTFUEL			1.0001	1.0001	1.0001	1.0001
DISTLEI					1.0059***	1.0058***
FREQLEI					0.9520	0.9483
DISTCOM			1.0315*	1.0310*	1.0233	1.0223
FREQCOM			1.0021	1.0050	0.9811	0.9988
WORK			0.6600	0.6670	0.9147	0.8969
STUDY			3.7455*	3.8995*	2.6326	2.9189
SHOPPING			0.8188	0.8208	1.7270	1.6549
CUT1	7.4753	15.7592	16.5682	15.5665	19.3333	17.4546
CUT2	9.7682	18.2701	19.1244	18.1395	22.0308	20.1671
CUT3	11.2854	19.8966	20.7684	19.7943	23.8266	21.9642
Wald Chi^2	130.0802***	123.4585***	151.7148***	150.8615***	126.2714***	127.5465***
Pseudo R^2	0.1844	0.2664	0.2854	0.2887	0.3195	0.3206
N	825	825	812	812	463	463

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at the 10%, 5% and 1% level.

We continue by describing in detail the role of the urban form and travel characteristics in determining the ownership of motorcycles and cars. We refer to Appendix B.2 for a detailed description of how travellers' personal and household characteristics affect the ownership of motorcycles and cars.

Table 6.13 – Marginal Effect of the OLR on Motorcycle Ownership

Explanatory Variables	Model A13				Model A14				Model B17			
	None	1–2 Units	3–4 Units	5–7 Units	None	1–2 Units	3–4 Units	5–7 Units	None	1–2 Units	3–4 Units	5–7 Units
FEMALE	0.0273	0.0716	−0.0849	−0.0140	0.0290*	0.0687*	−0.0828*	−0.0148*	0.0313*	0.0718*	−0.0873*	−0.0158*
AGE	0.0022***	0.0057***	−0.0068***	−0.0011***	0.0024***	0.0057***	−0.0068***	−0.0012***	0.0021***	0.0048***	−0.0058***	−0.0011***
EDU	−0.0105***	−0.0276***	0.0327***	0.0054**	−0.0063*	−0.0149*	0.0179*	0.0032*	−0.0082**	−0.0189**	0.0230**	0.0041**
LNINCCAP					−0.0216***	−0.0512***	0.0617***	0.0111***	−0.0223***	−0.0510***	0.0621***	0.0112***
HHSIZE					−0.0595***	−0.1412***	0.1702***	0.0305***	−0.0615***	−0.1410***	0.1716***	0.0310***
YOUNG CHILD	0.0161	0.0423	−0.0501	−0.0083	0.0674***	0.1599***	−0.1927***	0.0345***	0.0589***	0.1349***	−0.1641***	−0.0296***
OLDER CHILD	0.0033	0.0088	−0.0104	−0.0017	0.0460***	0.1091***	−0.1315***	−0.0236***	0.0444***	0.1017***	−0.1238***	−0.0224***
CAROWN	−0.0193**	−0.0505**	0.0599**	0.0099**	−0.0067	−0.0160	0.0193	0.0035	−0.0050	−0.0114	0.0139	0.0025
BIKEOWN	−0.0090*	−0.0237**	0.0281**	0.0046*	0.0004	0.0010	−0.0012	−0.0002	0.0024	0.0054	−0.0066	−0.0012
CBD									−0.0004	−0.0009	0.0011	0.0002
LNDENSITY												
URBAN									0.0120	0.0276	−0.0336	−0.0061
RURAL									0.0050	0.0115	−0.0140	−0.0025
DISTPUB									−2.3e-6	−5.3e-6	6.4e-6	1.2e-6
DISTFUEL									−2.0e-6	−4.5e-6	5.4e-6	9.8e-6
DISTLEI												
FREQLEI												
DISTCOM									−0.0005	−0.0011	0.0013	0.0002
FREQCOM									0.0042	0.0097	−0.0118	−0.0021
WORK									−0.0635**	−0.1455***	0.1770***	0.0320**
STUDY									−0.0604**	−0.1384**	0.1684**	0.0304**
SHOPPING									−0.0477	−0.1094*	0.1331*	0.0240

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at 10%, 5% and 1% level.

Table 6.13 – Marginal Effect of the OLR on Motorcycle Ownership (continued)

Explanatory Variables	Model B18				Model B19				Model B20			
	None	1–2 Units	3–4 Units	5–7 Units	None	1–2 Units	3–4 Units	5–7 Units	None	1–2 Units	3–4 Units	5–7 Units
FEMALE	0.0306*	0.0700*	−0.0853*	−0.0153*	0.0380*	0.1073*	−0.1235*	−0.0218*	0.0379*	0.1070*	−0.1232*	−0.0217*
AGE	0.0021***	0.0048***	−0.0058***	−0.0010***	0.0012**	0.0034**	−0.0039**	−0.0007 **	0.0012**	0.0034**	−0.0039**	−0.0007**
EDU	−0.0083**	−0.0191**	0.0232**	0.0042**	−0.0099**	−0.0280**	0.0332**	0.0057**	−0.0098**	−0.0278**	0.0320**	0.0056**
LNINCCAP	−0.0226***	−0.0517***	0.0629***	0.0113***	−0.0135*	−0.0381**	0.0438**	0.0078*	−0.0137*	−0.0386**	0.0445**	0.0078*
HHSIZE	−0.0616***	−0.1412***	0.1719***	0.0309***	−0.0521***	−0.1472***	0.1693***	0.0300***	−0.0522***	−0.1475***	0.1697***	0.0299***
YOUNGCHILD	0.0589***	0.1350***	−0.1643***	−0.0296***	0.0449***	0.1269***	−0.1460***	−0.0258***	0.0449***	0.1268***	−0.1460***	−0.0257***
OLDERCHILD	0.0448***	0.1027***	−0.1251***	−0.0225***	0.0298***	0.0843***	−0.0970***	−0.0172***	0.0302***	0.0854***	−0.0983***	−0.0173***
CAROWN	−0.0048	−0.0110	0.0134	0.0024	−0.0027	−0.0075	0.0086	0.0015	−0.0025	−0.0070	0.0080	0.0014
BIKEOWN	0.0023	0.0054	−0.0065	−0.0012	−0.0023	−0.0066	0.0075	0.0013	−0.0024	−0.0068	0.0078	0.0014
CBD					−0.0004	−0.0010	0.0012	0.0002				
LNDENSITY	0.0057	0.0131	−0.0160	−0.0029					0.0031	0.0087	−0.0100	−0.0018
URBAN	0.0106	0.0243	−0.0296	−0.0053	0.0018	0.0051	−0.0058	−0.0010	0.0016	0.0046	−0.0053	−0.0009
RURAL	0.0069	0.0159	−0.0194	−0.0035	0.0176	0.0498	−0.0573	−0.0101	0.0178	0.0503	−0.0579	−0.0102
DISTPUB	−2.1e-6	−4.9e-6	5.9e-6	1.1e-6	−4.2e-6	−1.2e-5	1.4e-5	2.4e-6	−4.1e-6	−1.2e-5	1.3e-5	2.3e-6
DISTFUEL	−2.0e-6	−4.5e-6	5.4e-6	9.8e-7	−1.4e-6	−4.1e-6	4.7e-6	8.3e-7	−1.6e-6	−4.6e-6	5.3e-6	9.3e-7
DISTLEI					0.0001	0.0002	−0.0003	−4.5e-5	0.0001	0.0002	−0.0003	−4.6e-5
FREQLEI					−0.0004	−0.0010	0.0012	0.0002	−0.0003	−0.0008	0.0010	0.0002
DISTCOM	−0.0004	−0.0009	0.0011	0.0002	−0.0007	−0.0021	0.0024	0.0004	−0.0007	−0.0020	0.0024	0.0004
FREQCOM	0.0040	0.0092	−0.0112	−0.0020	−0.0009	−0.0025	0.0029	0.0005	−0.0011	−0.0030	0.0034	0.0006
WORK	−0.0638**	−0.1463***	0.1781***	0.0320**	−0.0630**	−0.1781**	0.2049**	0.0363**	−0.0630**	−0.1781**	0.2049**	0.0361**
STUDY	−0.0621**	−0.1423**	0.1732**	0.0312**	−0.0528	−0.1493*	0.1717*	0.0304	−0.0535	−0.1512*	0.1740*	0.0306
SHOPPING	−0.0479	−0.1099*	0.1338*	0.0241	−0.0491	−0.1389	0.1598	0.0283	−0.0494	−0.1397	0.1607	0.0283

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at 10%, 5% and 1% level.

Table 6.14 – Marginal Effect of the OLR on Car Ownership

Explanatory Variables	Model A15				Model A16				Model B21			
	None	1 Unit	2 Units	3–4 Units	None	1 Unit	2 Units	3–4 Units	None	1 Unit	2 Units	3–4 Units
FEMALE	−0.0022	0.0016	0.0004	0.0001	0.0040	−0.0029	−0.0008	−0.0003	0.0177	−0.0128	−0.0036	−0.0013
AGE	−1.0e-5	7.7e-6	1.9e-6	7.1e-7	−1.8e-5	1.3e-5	3.7e-6	1.3e-6	−0.0016	0.0011	0.0003	0.0001
EDU	−0.1212***	0.0903***	0.0226***	0.0083***	−0.0675***	0.0492***	0.0135***	0.0048***	−0.0713***	0.0515***	0.0145***	0.0054***
LNINCCAP					−0.1725***	0.1258***	0.0345***	0.0123**	−0.1568***	0.1132***	0.0318***	0.0118***
HHSIZE					−0.0346**	0.0252**	0.0069**	0.0025*	−0.0316**	0.0228**	0.0064*	0.0024*
YOUNGCHILD	−0.1003***	0.0747***	0.0187***	0.0069***	−0.0749**	0.0546**	0.0150**	0.0053**	−0.0837***	0.0604***	0.0170***	0.0063**
OLDERCHILD	−0.1246***	0.0928***	0.0232***	0.0085**	−0.1003***	0.0731***	0.0200***	0.0071**	−0.0767***	0.0553***	0.0155***	0.0058**
MOCYOWN	−0.0361***	0.0269***	0.0067***	0.0025**	−0.0176	0.0128	0.0035	0.0012	−0.0164	0.0118	0.0033	0.0012
BIKEOWN	−0.0010	0.0007	0.0002	0.0001	−0.0026	0.0019	0.0005	0.0002	−0.0040	0.0029	0.0008	0.0003
CBD									−0.0011	0.0008	0.0002	0.0001
LNDENSITY												
URBAN									−0.0036	0.0026	0.0007	0.0003
RURAL									0.0801*	−0.0578*	−0.0162*	−0.0060
DISTPUB									−1.2e-5	8.4e-6	2.4e-6	8.8e-7
DISTFUEL									−6.2e-6	4.5e-6	1.3e-6	4.7e-7
DISTLEI												
FREQLEI												
DISTCOM									−0.0032*	0.0023*	0.0007*	0.0002
FREQCOM									−0.0002	0.0002	4.5e-5	1.7e-5
WORK									0.0434	−0.0313	−0.0088	−0.0033
STUDY									−0.1378*	0.0995*	0.0279	0.0104
SHOPPING									0.0209	−0.0151	−0.0042	−0.0016

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at 10%, 5% and 1% level.

Table 6.14 – Marginal Effect of the OLR on Car Ownership (continued)

Explana-tory Variables	Model B22				Model B23				Model B24			
	None	1 Unit	2 Units	3–4 Units	None	1 Unit	2 Units	3–4 Units	None	1 Unit	2 Units	3–4 Units
FEMALE	0.0169	−0.0122	−0.0034	−0.0013	0.0237	−0.0156	−0.0058	−0.0023	0.0234	−0.0155	−0.0057	−0.0022
AGE	−0.0016	0.0012	0.0003	0.0001	−0.0011	0.0007	0.0003	0.0001	−0.0014	0.0009	0.0003	0.0001
EDU	−0.0712***	0.0515***	0.0144***	0.0054***	−0.0790***	0.0520***	0.0194***	0.0076**	−0.0793***	0.0524***	0.0193***	0.0076**
LNINCCAP	−0.1570***	0.1135***	0.0317***	0.0118***	−0.2210***	0.1455***	0.0544***	0.0212**	−0.2212***	0.1462***	0.0538***	0.0212**
HHSIZE	−0.0318**	0.0230**	0.0064*	0.0024*	−0.0536***	0.0352***	0.0132**	0.0051*	−0.0539**	0.0356**	0.0131**	0.0052*
YOUNGCHILD	−0.0833***	0.0602***	0.0168***	0.0063**	−0.0863**	0.0568*	0.0212*	0.0083	−0.0871**	0.0576*	0.0212*	0.0083*
OLDERCHILD	−0.0755***	0.0545***	0.0152***	0.0057**	− 0.1086***	0.0715***	0.0267***	0.0104**	−0.1058***	0.0699***	0.0257***	0.0101**
MOCYOWN	−0.0161	0.0117	0.0033	0.0012	−0.0175	0.0115	0.0043	0.0017	−0.0175	0.0116	0.0043	0.0017
BIKEOWN	−0.0045	0.0032	0.0009	0.0003	0.0088	−0.0058	−0.0022	−0.0008	0.0084	−0.0055	−0.0020	−0.0008
CBD					−0.0018	0.0012	0.0004	0.0002				
LNDENSITY	0.0111	−0.0080	−0.0022	−0.0008					0.0269	−0.0178	−0.0065	−0.0026
URBAN	−0.0049	0.0035	0.0010	0.0004	−0.0071	0.0047	0.0017	0.0007	−0.0140	0.0093	0.0034	0.0013
RURAL	0.0825*	−0.0596*	−0.0167*	−0.0062	0.0954	−0.0628	−0.0235	−0.0091	0.0997	−0.0659	−0.0242	−0.0096
DISTPUB	−1.1e-5	8.2e-6	2.3e-6	8.6e-7	−1.6e-6	1.1e-7	3.9e-7	1.5e-7	−3.8e-7	2.5e-7	9.3e-8	3.7e-8
DISTFUEL	−6.6e-6	4.8e-6	1.3e-6	5.0e-7	−1.4e-5	8.9e-6	3.3e-6	1.3e-6	−1.3e-5	8.7e-6	3.2e-6	1.3e-6
DISTLEI					−0.0007***	0.0004***	0.0002***	0.0001***	−0.0007***	0.0004***	0.0002***	0.0001**
FREQLEI					0.0057	−0.0037	−0.0014	−0.0005	0.0061	−0.0041	−0.0015	−0.0006
DISTCOM	−0.0032*	0.0023*	0.0006*	0.0002	−0.0027	0.0018	0.0007	0.0003	−0.0025	0.0017	0.0006	0.0002
FREQCOM	−0.0005	0.0004	0.0001	3.9e-5	0.0022	−0.0015	−0.0005	−0.0002	0.0001	−0.0001	−3.3e-5	−1.3e-5
WORK	0.0423	−0.0305	−0.0085	−0.0032	0.0103	−0.0068	−0.0025	−0.0010	0.0126	−0.0083	−0.0031	−0.0012
STUDY	−0.1421*	0.1027*	0.0287*	0.0107	−0.1120	0.0737	0.0275	0.0107	−0.1239	0.0819	0.0301	0.0119
SHOPPING	0.0206	−0.0149	−0.0042	−0.0016	−0.0632	0.0416	0.0156	0.0061	−0.0583	0.0385	0.0142	0.0056

Notes: (1) Robust standard errors are not displayed. (2) *, ** and *** = significant at 10%, 5% and 1% level.

Urban Form and Travel Characteristics

Our results show that the impact of the distance between the home and the city centre on the household ownership of private motor vehicles is insignificant (see Model B9 and Model B11 in Table 6.11 and Model B13 and Model B15 in Table 6.12). Furthermore, we find that urban and rural areas have no significant effect on the household ownership of a motorcycle (see Table 6.11). Households that live in rural areas have a lower significant probability of owning a car than those that live in peri-urban areas (see Table 6.12). Rural areas increase the likelihood of owning no car by 8.0%–8.3% and decrease the tendency to have 1 or 2 cars, respectively, by 5.8%–6.0% and 1.6%–1.7% (see Models B21–B22 in Table 6.12).

In contrast to our results for the transport mode choice, the population density has no significant effect on the household ownership of private motor vehicles (see Tables 6.11–6.14). In addition, the distance from home to a public transport stop has no significant effect on the household ownership of private motor vehicles (see Tables 6.11–6.14). Similarly, the travel frequency has no significant effect on the household ownership of private motor vehicles (see Tables 6.11–6.14) – in contrast to the transport mode choice.

Furthermore, we find that the travel distance does not influence the household ownership of motorcycles but, for commuting and leisure activities, it does affect the household ownership of a car. A household with a 1 kilometre longer average travel distance has a 0.3% lower probability of not having any car but a 0.2% higher probability of having 1 car and a 0.06–0.07% higher probability of owning 2 cars for commuting (see Models B21–B22 in Table 6.14). For leisure activity, a household with a 1 kilometre longer average travel distance has a 0.07% lower probability of not having any car while having a higher probability of having 1 car, 2 cars and 3–4 cars of, respectively, 0.04%, 0.02% and 0.01% (see Models B23–B24 in Table 6.14).

Finally, the number of household members who engage in work, study and shopping activities has a positive significant effect on the probability of having a motorcycle (see Table 6.11). The number of household members who have study activity increases the probability of car ownership by the household (see Table 6.12). More precisely, the number of household members who undertake work, study and shopping activities has a negative significant effect on the probability of not having any motorcycle or having 1–2 motorcycles. In contrast, a 1% increase in the number of household members who have work, study and shopping activities raises the probability of having 3–4 motorcycles by, respectively, 17.7%–20.5%, 16.8%–17.4% and 13.3%–13.4%. A 1% increase in the number of household members who have work and study activities also increases the probability of having 5–7 motorcycles, respectively, by 3.2%–3.6% and 3.0%–3.1% (see Models B13–B16 in Table 6.13). Overall, most of the indicators for urban form do not have an influence on motor vehicle ownership, except for rural areas, which have a negative significant effect on car ownership. All the main commuting activities, that is, work, study and shopping, have a large effect on the ownership of 3–4 motorcycles. However, for car ownership, study activity has the greatest influence on the ownership of 1 car.

6.6 Conclusions

In this chapter, we presented the results from a field study conducted in the metropolitan area of Yogyakarta in Indonesia, in which we analysed the influence of urban form on motorcycle choice in comparison with other transport modes. We also examined the impact of urban form on households' ownership of motorcycles in comparison with cars.

Our data came from a survey about energy consumption and travel behaviour that we conducted in 2016 with 823 households in different areas of the metropolitan area of Yogyakarta, on the island of Java in Indonesia. To assess how the urban form influences preferences for the use of motorcycles, we employed a multinomial logistic (MNL) regression model. To determine how the urban form influences preferences for the ownership of motorcycles, we used an ordinal logit regression (OLR) approach. We corrected in our regression analyses for the influence of personal and household characteristics, such as gender, education level, income and household size. Furthermore, in our analyses, we distinguished between travelling for commuting and travelling for leisure purposes.

We found that the urban form explains about 20% of the observed variance in transport mode choice, while it explains less than 6% of the observed variance in the probability of household ownership of motorcycles and cars. More specifically, we found that the population density has a statistically significant positive effect on the likelihood of using a motorcycle in commuting. A decrease in the population density by 1% decreases the tendency to use a motorcycle by 0.035% and increases the probability of cycling by 2.4%. In addition, we found that the travel distance affects the likelihood of using a motorcycle in commuting. People who live near the city centre have a higher probability of travelling by car than by motorcycle; in contrast, people who live far from the city centre have a higher tendency to travel by bicycle than by motorcycle. In other words, the likelihood of choosing a motorcycle over other transport modes is highest for intermediate distances between the home and the city centre. This distance effect, however, is relatively small: an increase of 1 kilometre in the distance between the house and the city centre reduces the probability of a commuter driving a car by 0.26% and increases the probability of commuting by cycling by 0.18%. Furthermore, the results of our regression analyses revealed that, for both commuting and leisure activities, motorcycle use is the most sensitive to travel distance. For commuting activity, one kilometre increase in the travel distance increases the probability of using a motorcycle by 10.34% compared with 0.5%, 0.6% and 1.6% for, respectively, a bus, car and bicycle. For leisure activity, these marginal effects are slightly lower.

Furthermore, we found that the travel frequency increases the likelihood of travelling by motorcycle. For commuting activity, an increase of 1 trip per week increases the probability of using a motorcycle by 1.25%–1.34% and decreases the chance of choosing to travel by bus and car, respectively, by about 0.4% and 1.0%. For leisure travel, these marginal effects are slightly higher. Our results also show that, for commuting activity, the distance from home to a public transport stop has a significant negative impact on the tendency to use the bus and a positive significant effect on the likelihood of using a car compared with a motorcycle. The distance from home to the fuel station does not affect commuters' transport mode choice.

In contrast to our results for the transport mode choice, the population density has no significant effect on households' ownership of private motor vehicles, including motorcycles. In addition, the impact of the distance between the home and the city centre on the household ownership of private motor vehicles appears to be insignificant. We also found that the travel distance in general does not influence the household ownership of motorcycles, but it does exert a positive impact on the ownership of a car. Furthermore, we found – in contrast to the transport mode choice – that the travel frequency has no significant effect on the household ownership of private motor vehicles.

As in much of Asia, the motorcycle is by far the dominant mode of urban transport in Yogyakarta; 95% of the households in Yogyakarta own a motorcycle and almost 30% of the households own more than 2 motorcycles. Motorcycles are the preferred transport mode for 66% of the commuters in Yogyakarta and based on our survey, motorcycle contributes to 66% of total CO_2 emission that comes from transport. For buses and bicycles, this percentage is, respectively, 2% and 9%. Hence, encouraging substitution away from the usage of private motorized vehicles towards public transportation or non-motorized transport modes – with the aim of decreasing the energy consumption and emissions from transport – is evidently a huge challenge. In the Yogyakarta Metropolitan Area, an alternative mode of transport is the Trans-Jogya bus. Our results suggest that a compact urban form, including a high population density and short travel distances, may help in reducing the (growth of) motorcycle use in urban areas.

However, the strong dominance of motorcycles as the preferred mode of transport also makes it clear that it will be very difficult to motivate people to make bus services, like the one offered by the Trans-Jogya service, a good substitute for a motorcycle. An alternative long-term policy option is to encourage people to replace their conventional motorcycle with an electric motorcycle. Until now, the market share of electric motorcycles in Indonesia has been very small, due to an inadequate supporting infrastructure, the unclear regulation for electric vehicles, the relatively high price and the short lifetime of the battery for electric motorcycles/bicycles, the relatively long time required for refuelling compared with conventional motorcycles and the limited travel distance, power and speed (Jeghesta, 2016; Ravel, 2016). Thus, given the large number of motorcycles in urban areas in Indonesia, stimulating the growth of the market for electric motorcycles or even bicycles is in principle a potentially promising urban policy strategy. This, however, requires that the Government seriously develops the supporting infrastructure, such as providing charging units in public places, office centres and residential areas; increasing the number of dealers and service shops of electric motorcycles/bicycles, finishing the regulation formulation for electric motorcycles and considering the provision of subsidies to encourage people to purchase electric motorcycles/bicycles.

APPENDIX 6.A – Tables of Household Characteristics from Other Sources and Correlations among Variables in This Study

Table 6.15 – Comparison of Statistics from the Survey and Other Sources

	Survey in February 2016[2)]	Year	Other Sources
Motorcycles per 1,000 people[(1)]	588	2016	582[(a, b, c)]
Cars per 1,000 people [(1)]	71	2016	104[(a, b, c)]
% of households that own a motorcycle	74.94%	2014	68.32%[(d,3)]
% of households that own a car	0.85%	2014	0.33%[(d,3)]
% of households that own a motorcycle and car	19.25%	2014	12.59%[(d,3)]
Household members	3.492	2015	3.205[(e)]
% of males	50.82%	2016	49.82%[(a, b, c)]
% of females	49.18%	2016	50.18%[(a, b, c)]
% of people aged 15 years old or more, by education:			
No schooling and not yet completed primary school	5.49%	2016	13.46%[(f,3)]
Elementary school	14.51%	2016	17.78%[(f,3)]
Junior high school	19.36%	2016	19.24%[(f,3)]
Senior high school	43.73%	2016	36.06%[(f,3)]
Diploma/university	16.91%	2016	13.45%[(f,3)]

Notes: (1) For the survey data, the number of private motor vehicles per 1,000 people is calculated based on the number of private motor vehicles and total household members, and, for other sources, it is based on the number of private motor vehicles and the population. (2) Only for Yogyakarta City, Sleman Regency and Bantul Regency. (3) The value represents the figure for Yogyakarta Province, including Kulon Progo Regency and Gunung Kidul Regency.
Sources: Figures from other sources are taken or calculated based on figures from these sources: (a) Statistics of Yogyakarta Municipality (2017), (b) Statistics of Sleman Regency (2017), (c) Statistics of Bantul Regency (2017), (d) BPS Indonesia (2015), (e) Statistics of D.I. Yogyakarta Province (2016) and (f) Statistics of D.I. Yogyakarta Province (2017).

The table above demonstrates that most of the figures from our survey are close to the figures from other sources, which shows that the figures from our survey are reliable.

Table 6.16 – Correlation among Variables for Commuting Activity

	LNDISDEN	CBD	DIST	TIME	FREQ	DISTPUB	DISTFUEL	AGE	EDU	LNINCCAP	PRIVEMOCY	PRIVECAR
LNDISDEN	1.0000											
CBD	−0.7531 ***	1.0000										
DIST	−0.1624 ***	0.1525 ***	1.0000									
TIME	−0.0815 ***	0.0614 ***	0.6198 ***	1.0000								
FREQ	0.0448 **	−0.0153	−0.0032	0.0038	1.0000							
DISTPUB	−0.2518 ***	0.2871 ***	0.0623 ***	0.0229	0.0354	1.0000						
DISTFUEL	−0.3633 ***	0.5759 ***	0.1017 ***	0.0304	0.0070	0.3089 ***	1.0000					
AGE	0.0327	−0.0157	0.0002	0.0547 ***	−0.0831 ***	−0.0188	−0.0053	1.0000				
EDU	0.1030 ***	−0.1298 ***	0.2240 ***	0.1106 ***	−0.0509 **	−0.0591 ***	−0.0465 **	0.2571 ***	1.0000			
LNINCCAP	0.1443 ***	−0.1845 ***	0.1623 ***	0.0889 ***	−0.0451 **	−0.0617 ***	−0.1358 ***	0.0600 ***	0.3694 ***	1.0000		
PRIVEMOCY	−0.0578 ***	0.0367 *	0.0878 ***	−0.0068	0.0230	−0.0105	0.0235	−0.0771 ***	0.0915 ***	0.1514 ***	1.0000	
PRIVECAR	0.0383 *	−0.0750 ***	0.1148 ***	0.0620 ***	−0.0248	0.0396 **	−0.0011	−0.0376 *	0.2438 ***	.4025 ***	0.1525 ***	1.0000
PRIVEBICY	−0.1098 ***	0.1758 ***	−0.0268	0.0087	−0.0045	0.0387 *	0.0403 **	−0.0779 ***	−0.1474 ***	−0.1502 ***	0.0676 ***	−0.0159
HHSIZE	−0.0339 *	0.0316	−0.0521 ***	−0.0253	0.0385 *	−0.0220	0.0126	−0.1589 ***	−0.1542 ***	−0.2504 ***	0.4872 ***	0.0539 ***
YOUNGCHILD	−0.0630 ***	0.0764 ***	−0.0696 ***	−0.0295	−0.0094	0.0435 **	0.0863 ***	−0.1626 ***	−0.1076 ***	−0.1842 ***	0.0055	−0.0509 **
OLDERCHILD	−0.0595 ***	0.0341 *	−0.0624 ***	−0.0195	0.0321	0.0616 ***	0.0057	−0.2683 ***	−0.1965 ***	−0.1819 ***	0.0239	0.1093 ***

Note: *, ** and *** = significant at 10%, 5% and 1% level.

	PRIVEBICY	HHSIZE	YOUNGCHILD	OLDERCHILD
PRIVEBICY	1.0000			
HHSIZE	0.2902 ***	1.0000		
YOUNGCHILD	0.0824 ***	0.3769 ***	1.0000	
OLDERCHILD	0.3283 ***	0.4047 ***	0.0033	1.0000

Note: *, ** and *** = significant at 10%, 5% and 1% level.

Table 6.17 – Correlation among Variables for Leisure Activity

	LNDISDEN	CBD	DIST	TIME	FREQ	DISTPUB	DISTFUEL	AGE	EDU	LNINCCAP	PRIVEMOCY	PRIVECAR
LNDISDEN	1.0000											
CBD	−0.7620 ***	1.0000										
DIST	−0.0327	0.0300	1.0000									
TIME	−0.0481	0.0524	0.7576 ***	1.0000								
FREQ	0.0193	−0.0135	−0.1068 ***	−0.1380 ***	1.0000							
DISTPUB	−0.2874 ***	0.3061 ***	0.0561 *	0.0823 **	−0.0236	1.0000						
DISTFUEL	−0.4187 ***	0.5231 ***	0.0579 *	0.0320	−0.0035	0.4150 ***	1.0000					
AGE	0.0224	−0.0596 **	−0.0765 **	−0.0788 **	−0.0108	−0.0599 *	−0.0739 **	1.0000				
EDU	0.0746 **	−0.1344 ***	0.0050	−0.0008	0.0040	−0.0670 **	−0.0324	0.3389 ***	1.0000			
LNINCCAP	0.0948 ***	−0.1492 ***	0.1150 ***	0.1303 ***	−0.0253	−0.0181	−0.0849 ***	0.0346	0.3831 ***	1.0000		
PRIVEMOCY	−0.0563 *	0.0552 *	0.1174 ***	0.1177 ***	0.0516	0.0059	0.0488	−0.0816 **	0.0737 **	0.1036 ***	1.0000	
PRIVECAR	−0.0289	−0.0561 *	0.0857 ***	0.1229 ***	−0.1022 ***	0.0166	0.0738 **	−0.0401	0.2268 ***	0.4341 ***	0.1084 ***	1.0000
PRIVEBICY	−0.1477 ***	0.2137 ***	0.1192 ***	0.1322 ***	−0.0600 *	0.0060	0.0108	−0.1421 ***	−0.1809 ***	−0.1395 ***	0.1458 ***	0.0009
HHSIZE	−0.0440	0.0368	0.0396	0.0567 *	−0.0847 ***	−0.0436	0.0389	−0.1681 ***	−0.1371 ***	−0.2434 ***	0.4823 ***	0.1285 ***
YOUNGCHILD	−0.0209	0.1251 ***	−0.0173	0.0193	−0.1166 ***	0.0279	0.0587 *	−0.3114 ***	−0.1727 ***	−0.1764 ***	−0.0390	−0.0374
OLDERCHILD	−0.1049 ***	0.0083	0.0016	0.0225	−0.1280 ***	0.0327	0.0501	−0.2175 ***	−0.1557 ***	−0.1480 ***	0.0526	0.1817 ***

Note: *, ** and *** = significant at 10%, 5% and 1% level.

	PRIVEBICY	HHSIZE	YOUNGCHILD	OLDERCHILD
PRIVEBICY	1.0000			
HHSIZE	0.3272 ***	1.0000		
YOUNGCHILD	0.1694 ***	0.3199 ***	1.0000	
OLDERCHILD	0.3355 ***	0.3916 ***	−0.0396	1.0000

Note: *, ** and *** = significant at 10%, 5% and 1% level.

APPENDIX 6.B – The Role of Personal and Household Characteristics

B1. Transport Mode Choice

In this Appendix, we discuss the role of personal and household characteristics in explaining people's transport mode choice. The results show that, compared with male travellers, female travellers have a higher probability of walking than travelling by motorcycle (see Tables 6.7 and 6.8). For commuting activity, female commuters also tend to choose the bus over a motorcycle but prefer a motorcycle to a car (see Table 6.7).[53]

Age has a negative significant effect on the probability of travelling by motorcycle and positive significant effects on the probability of travelling by other transport modes (see Models B1–B2 in Table 6.7). Thus, motorcycles tend to be used by young commuters, while older commuters tend to choose other transport modes. For leisure activity, age also has a positive significant effect on the probability of travelling by cycling or walking rather than travelling by motorcycle (see Table 6.8).

Furthermore, our sample features a positive significant correlation between education and per capita income (see Figure 6.4 and Tables 6.16–6.17 in the Appendix). Thus, people with higher education tend to have a higher income. Our regression results show that, for commuting activity, a higher level of education stimulates travel by motorcycle rather than by bus, bicycle or walking and a higher level of income encourages commuters to choose a car over a motorcycle (see Model B1–Model B2 in Table 6.7). An increase of education by one level increases the probability of using a motorcycle by 3.3%–3.5%, while an increase in the natural logarithm of per capita income by 1% can decrease the likelihood of using a motorcycle by 0.032%–0.035% and raises the likelihood of using a car by 0.0224%–0.0237% (see Models B5–B6 in Table 6.9). Thus, a higher level of education or income increases the ability and the desire to choose a more comfortable or

[53] The effect on walking and cars compared with motorcycles confirms the result by Irawan and Sumi (2011b) for Yogyakarta and Marquet and Miralles-Guasch (2016) for Spain. In Jakarta, Yagi et al. (2014) found that male workers use motorcycles and cars significantly more often and public transportation less often. Regarding study activity, Yagi et al. (2014) found that male commuters tend to use a motorcycle while female commuters tend to utilize public transportation.

luxurious transport mode.[54] For leisure activity, education increases the probability of using a car relative to a motorcycle, while a rising income increases the probability of using a bus relative to a motorcycle (see Model B3–Model B4 in Table 6.8). Buses are more interesting than motorcycles in leisure activity, because driving a motorcycle is more exhausting than travelling by bus.[55]

Our results also show that the household size increases the probability of commuting by bus, bicycle or walking compared with using a motorcycle (see Models B1–B2 in Table 6.7). Regarding leisure activity, the household size decreases the probability of using a car or bicycle (see Models B3–B4 in Table 6.8). An increase in the household size by one person reduces the probability of commuters riding a motorcycle by 3.9%–4.1% (see Models B5–B6 in Table 6.9). For leisure activity, an increase in the household size by one person increases the likelihood of a traveller riding a motorcycle by 2.8%–2.9%, but it decreases the tendency of a traveller to drive a car by about 1.5% (see Models B7–B8 in Table 6.10).[56]

A higher number of young children increases the probability of travelling by motorcycle rather than by bicycle or walking for commuting (see Models B1–B2 in Table 6.7).[57] However, if a family has more than one child, it will be difficult to escort them to school by motorcycle when they grow older, given that a motorcycle is designed for only two passengers. Indeed, we find that an increasing number of older children raises the likelihood of travelling by car rather than by motorcycle. An increase of one young child in the family raises the tendency to use a motorcycle by 6.0%–6.2%, while an increase of one older child in the household increases the chance of travelling by car by 2.6%–2.7% (see Models B.5 and B.6 in Table 6.9).[58] For leisure

[54] These findings explain the results in Chapter 5 showing why education and income have a positive significant effect on the per capita energy use for transport (Fevriera & Mulder, 2017).

[55] In Spain, Marquet & Miralles-Guasch (2016) found that, in comparison with people whose educational background is primary school, those who have a college degree have a lower probability of using a bicycle, walking or driving a car relative to using a motorcycle. In Malaysia, Sheik et al. (2016) discovered that income increases the probability of travelling by motorcycle rather than by bus. For Taiwan, Chen & Lai (2011) found that income reduces the likelihood of travelling by motorcycle. In Jakarta, Yagi et al. (2014) discovered that income has a positive significant effect on the usage of cars and a negative significant effect on the usage of motorcycles for work activity, but for study activity it has a positive significant effect on the usage of cars and motorcycles.

[56] In China, Liu et al. (2016) discovered that the household size has a significant negative effect on the probability of travelling by motorcycle and bus.

[57] This result confirms the finding by Irawan & Sumi (2011b).

[58] In Jakarta, Yagi et al. (2014) found that children aged 5–17 years have a positive significant effect on non-motorized transport.

activity, families usually want to spend time and travel together. Hence, the number of children increases the probability of travelling by car than by motorcycle (see Models B3–B4 in Table 6.8). An additional child in the family raises the likelihood of using a car by 7.2%–7.3% and 7.6%–7.8% for a young and older child, respectively; it decreases the tendency to travel by motorcycle by 9.18%–9.57% and 8.90%–8.94% for a young and an older child, respectively (see Models B7–B8 in Table 6.10). The number of older children also increases the likelihood of walking than riding a motorcycle (see Models B3–B4 in Table 6.8). An additional older child in the household increases the probability of walking by 2.6%–2.8% (see Models B7–B8 in Table 6.10).

Finally, we find that study and shopping activities influence the transport mode preference for commuting activity (see Models B1–B2 in Table 6.7). A 1% increase in the number of household members who have a study activity decreases the probability of using a car and a motorcycle, respectively, by about 4.6% and 20% and increases the probability of using a bicycle by about 22% (see Models B.5 and B.6 in Table 6.9). A 1% increase in the number of household members who have a shopping activity decreases the probability of using a car and a motorcycle, respectively, by about 4.2% and 12% (see Models B5–B6 in Table 6.9). Compared with motorcycles, the number of household members who have study and shopping activities has a positive effect on the probability of using a bicycle. The number of household members who engage in shopping activity also has a positive effect on the probability of walking, whereas it has a negative effect on the probability of using a car.[59]

Among the personal and household characteristics, the factor that makes the largest contribution to motor vehicle usage in commuting activity is motor vehicle ownership. Motor vehicle ownership is influenced by education and per capita income. Therefore, education and per capita income have quite a large effect on the motor vehicle preference.

[59] The positive effect of shopping activity on the probability that a bicycle will be chosen supports the finding by Buehler (2011) for Germany but contradicts his finding for the United States. However, instead of using motorcycles, he used cars as a reference.

B2. Ownership of motorcycles and cars

Our results show that the percentage of female members in the household has no influence on the probability of car ownership (see Table 6.12), but it has a negative significant effect on the probability of the household's motorcycle ownership (see Table 6.11).[60]

We find that the number of children increases the chance that a household will have a car or a motorcycle. An increase in the number of children in a family increases the probability of having at least 3 motorcycles and increases the probability of having at least 1 car. However, it decreases the probability of owning no motorcycle or a maximum of 2 motorcycles and decreases the probability of having no car. In addition, 1 additional young child in the family raises the probability of having 1–2 motorcycles by 12.7%–13.5% and owning 1, 2 and 3–4 cars, respectively, by 5.7%–6.0%, 1.7–2.1% and 0.6%–0.8%. Furthermore, 1 additional older child in the family raises the probability of having 1–2 motorcycles by 8.4%–10.3% and owning 1, 2 and 3–4 cars, respectively, by 5.5%–7.2%, 1.5–2.7% and 0.6%–2.6%.

The household size has a positive significant effect on the probability of private motor vehicle ownership (see Tables 6.11 and 6.12). It decreases the probability of having fewer than 3 motorcycles or no car, but an increase in the household size by 1 person increases the likelihood of having 3–4 motorcycles by about 17% while raising the chance of having 1 car by 2.3%–3.6% (see Models B17–B20 in Table 6.13 and Models B21–B24 in Table 6.14). In addition, we find that the household size causes the effects of the number of children in the household to become significant in the model of household ownership of motor vehicles (see Tables 6.11 and 6.13). Adding the per capita income to the model makes the effects of car and bicycle ownership become insignificant in the model of household ownership of motorcycles (see Tables 6.11 and 6.13), and it makes the effect of motorcycle ownership insignificant in the model of car ownership (see Tables 6.12 and 6.14). This might be caused by the fact that the household size is related to the number of children in the household, while vehicle ownership reflects a household's economic level. In other models, including

[60] Marquet and Miralles-Guasch (2016) also discovered that female travellers have a negative significant effect on the probability of having access to a motorcycle.

the household size and per capita income does not change the effects of the number of children and the number of vehicles owned.

Our results show that the average age of household members has a negative significant effect on the number of motorcycles owned by households. In other words, age reduces the probability that a household owns a motorcycle (see Table 6.11). However, we also find that age has no influence on the probability of owning a car (see Table 6.12).

We find that education and income decrease the probability of having no motorcycles or 1–2 motorcycles, while they increase the likelihood of owning more than 2 motorcycles or at least 1 car (see Table 6.13 and Table 6.14). An increase in the average education of household members by 1 level increases the probability of having 3–4 motorcycles by 2.3%–3.3% (see Models B17–B20 in Table 6.13) and the probability of having 1 or 2 cars, respectively, by 1.4%–1.9% and 5.2% (see Models B21–B24 in Table 6.14).

The number of motorcycles, cars and bicycles owned by a household increases the likelihood that travellers will travel by, respectively, motorcycle, car and bicycle (see Models B5–B6 in Table 6.9) but, for leisure activity, the number of cars owned by a household decreases the tendency of travellers to use a motorcycle (see Models B7–B8 in Table 6.10). Car and bicycle ownership have an insignificant effect on the probability of a household having a motorcycle, and motorcycle and bicycle ownership has an insignificant effect on the probability that a household owns a car.

Among the personal and household characteristics, the factor that has a large effect on the ownership of 1–2 motorcycles or 3–4 motorcycles is the number of children in the household. Hence, the household size also has a strong influence. For car ownership, the factor that has the greatest effect on the ownership of 1 car is income.

CHAPTER 7 Conclusions

In this thesis we studied several aspects of interactions between global environmental change, economic development and the structure of the economic system in developing countries. Our research focussed on Asian countries, and in particular on Indonesia. Indonesia is given its size and location an important country to study when thinking about interactions between global environmental change, economic development and the structure of the economy of developing countries. Indonesia is not only the world's fourth biggest country in terms of population size, but also its growth rates of both population and per capita GDP are higher than the world average. Between 1971 and 2014, Indonesia's energy use grew with 543 percent, against a 178 percent growth of energy use at the world level. Energy intensity in Indonesia is declining, but this decline is slower than the world average. Hence, the role of Indonesia in the world economy – including its contribution to global emissions and thus environmental change – is increasing over time. In this chapter we reflect upon the main findings of our analyses and suggest some avenues for future research.

7.1 On the Income-Emission Relationship

We started this thesis with an analysis of the relationship between economic development and environmental degradation. Chapters 2 and 3 emphasize the huge global challenge of fighting climate change in view of the development of emerging countries that are rapidly catching up with the developing world, amongst others resulting in substantial reductions in poverty. In Chapter 2 we presented a meta-analysis of previously published empirical studies on the Environmental Kuznets Curve (EKC) to shed new light on the long-lasting debate on the income–emission relationship (IER). More specifically, we wanted to explain the sources of variation in the shape of the EKC and its turning points. In contrast to previous studies, we focussed on CO_2 emissions as the main source of global warming, which helped improving the comparability of results across the studies included in our meta-analysis. Compared to existing meta-analyses published in the literature to date, we constructed a relatively large dataset, developed a dependent variable with a more refined classification of the possible shapes of the income-emission relationship, and applied both an ordered logit (ORL) and an Ordinary Least Squares (OLS) model while differentiating between maximum and minimum turning points of the income-emission relationship.

In Chapter 3 we aimed to identify the role of cultural values in a society in determining income-emission relationships (IERs) across a sample of Asian economies. Since CO_2 emissions result from human activities, cultural values can be thought of as (implicit) drivers of CO_2 emissions. Hence, the inverted U-shaped pattern that characterizes the EKC is also often implicitly assumed to be driven by cultural values. Analyses of the statistical relationship between environmental and cultural variables are scarce in the economic literature – with the study by Park et al. (2007) as an important exception. In contrast to Park et al. (2007), we explained per capita CO_2 emissions rather than using a composite environmental sustainability index and we improved the measurement of culture by adding two new cultural variables, following more recent work by Hofstede (2018). Rather than analysing a very heterogeneous sample of countries, we chose to focus our analysis on the most important emerging economies in Asia: Bangladesh, China, India, Indonesia, Malaysia, Myanmar, Pakistan, the Philippines and Thailand. Together, these countries comprise almost 50% of the world's population and are responsible for most of the global increase in global greenhouse gas emissions over the last decades (World Bank, 2018).

Our meta-analysis yielded evidence supporting the EKC hypothesis. As GDP level increases, studies with positive slope of IER curve decreases. Thus, most studies found negative slope of IER curve at high level of GDP. In general, the quality of a study and the selection of control variables affects the probability of finding evidence in favor of the EKC theory. The probability is higher in low-quality studies (defined as studies published in non-prominent journals, with a small sample size or covering only a short period of time) and in highly quality studies (defined as studies published in high rank journals). The probability also, for example, increases when a study employs control variables only from developed countries and related to trade or environment. In addition, we found that the quality of a study, the type of data used in a study, the method of analysis and the selection of control variables influence the maximum turning points in the IER relationship. Low predicted maximum turning points in the IER relationship – implying that environmental improvement (decrease of pollution) starts at a lower level of per capita income (an earlier development phase). Low predicted maximum turning points, for example, tend to be found in studies that published in high rank-journals, use a large sample size, a time trend or control variables related to population and energy.

Our analysis of the role of cultural values in determining income-emission relationships (IER) across a sample of Asian economies showed that per capita income and population size have a statistically significant positive effect on the CO_2 emission intensity whereas technological progress in the emerging Asian countries significantly reduces CO_2 emissions' intensity. Despite the fact that technological change tends to decrease CO_2 emissions' intensity, our results reject the existence of an EKC in the countries of our sample: instead, we found an increasing non-linear relation between per capita income and CO_2 emission intensity. Furthermore, we found evidence that the CO_2 emission intensity can be reduced through greater usage of clean energy, but is likely to increase with continued urbanization. Interestingly, we found that cultural variables significantly influence the CO_2 emission intensity. When CO_2 emission intensity is corrected for income, countries with a high individualism versus collectivism index and a high long-term versus short-term orientation index tend to have a low CO_2 emission intensity. Without income correction, societies featuring a high power distance index, a high uncertainty avoidance index, a low masculinity versus femininity index and a low indulgence versus restraint index also tend to have a low CO_2 emission intensity.

The lack of evidence for an inverted U-shaped relationship between development and emissions undermines the (implicit) idea that economic development will 'automatically' solve for today's pressing environmental concerns. Hence, it is a rational strategy for governments of emerging countries, including Indonesia, to focus on reducing the CO_2 emission intensity of their economic processes. Indonesia has some potential for alternative clean energy (Hutapea, 2015) resulting the Indonesian government to set a target to increase the share of new and renewable energy from 6% in 2014 to 23% in 2025 (Wibowo, 2015). A problem that is oftentimes faced by low-income and emerging countries, like Indonesia, is the lack of access to clean (energy) technologies.

Indonesia needs a lot of funding to meet the climate change targets and the Green Climate Fund (GCF) may help to overcome this problem (Insider, 2019). In October 2019, some countries committed to prepare some funds for the GCF for the next four years (GCF, 2019). GCF is a financial mechanism under United Nations Framework Convention on Climate Change (UNFCCC) that gives financial supports for developing countries in their efforts to reach the targets in the Paris Agreement signed in 2016, that is to have a better environment and to restrain the climate change (UNCC, 2019). The aids are expected to stimulate the emerging countries in achieving sustainable development. Sasmojo (2004), however, has emphasized that in the process of technology diffusion each piece of information in science and technology contains cultural dimensions from the society where that science and technology was developed. Different cultures may result in different ways of thinking and different behavior. This sometimes can result in failing adoption processes. Therefore, adaptation might be needed in the adoption process. The results of Chapter 3 suggest that the research into the cultural dimensions of clean energy diffusion deserves more attention in future work.

A different barrier to large-scale adoption and diffusion of clean energy practices in developing countries is that renewable energy often cannot compete with fossil fuels (DGNREEC-RI, 2012). The Indonesian government is still giving subsidy to energy for transport sector, electricity and cooking, but has been gradually reduced the subsidy. Efforts by the Indonesian government to revoke these energy subsidies always encountered many opponents. One of the objections is that rising energy prices contribute to inflation, which will put an extra burden on poor people. Furthermore, inflation will reduce the purchasing power of consumers and this may force producers to cut back production and lay off some of their employees.

Despite those objections and our finding that the increase of energy price could reduce per capita CO_2 emissions, many studies have shown that an energy subsidy will finally bring difficulties for the government, given the burden on the government budget. Realizing those problems, in January 1, 2015, the Indonesian government under Joko Widodo presidential ordered to eliminate the gasoline subsidy and the Indonesia government will evaluate fuel prices every month (Sambijantoro, 2015). Starting in 2016 the government also has been cutting the electricity subsidy and increasing the electricity price gradually (Anam, 2015). The electricity subsidy is only given to customers with lower power subscription. However, the government is planning to distribute the subsidy directly in cash to poor customers (Putri & Anam, 2015) because previously, the subsidy was enjoyed by all customer when actually, not all of the customers are poor and there is an indication that customers with higher electricity power subscription change to lower electricity power in order to gain subsidy (Fajriah, 2015). The subsidy reduction for electricity should enable PLN, the Indonesian government's electricity company, to make new investments to build new power stations, to add electricity networks, and to keep an adequate maintenance, because for some years PLN was forced by the government to sell the electricity below its economic value. This should also stimulate the development of clean energy because in 2012 the Indonesian government had released a regulation to prohibit the construction of oil fuel-fired power plants (MEMR-RI, 2012). In addition, the Indonesian government has abandoned its subsidy for 12 kg LPG canister. However, since the implementation of this policy there is a tendency that many customers of 12 kg LPG canister moved to 3 kg subsidized LPG canister. Therefore, the government is planning to change the subsidy system by implementing new distribution method (Wicaksono, 2018).

7.2 On the Role of Urbanization

Probably the most prominent feature of spatial transformation in developing countries is the rapid urbanization. The clustering of people and firms in urban areas causes cities to act as engines of local, national and global economic growth. However, the transition to a predominantly urban society will have a substantial impact on the global energy consumption and therefore on emissions.

In Chapter 4 we analyze the role of urbanization in the trade-off between greening and brown expansion of the electricity supply in developing countries. This idea starts from the notion that there are fundamental physical limits to how much energy we can extract from renewable resources for a given area of land. Fossil fuels are more power dense and hence spatially more productive than renewable energy resources (like solar), which, all things being equal, implies that it is cheaper to transport fossil fuels. If people, because of urbanization processes, are increasingly concentrated in space, the demand for resources with relatively high 'spatial productivity' will increase, thus impeding the emergence of a low-carbon energy system. In Chapter 4 developed a spatial energy model to analyze how the cost advantage of fossil fuels vis-à-vis low-carbon alternatives arises from three interrelated features: geography, power density and technology. We calibrated our model to the case of Indonesia.

We found, amongst others, that in a theoretical equilibrium the level of brown electricity produced increases in population density. In contrast, the level of green electricity produced increases, amongst others, with the efficiency rate of green power production, the power density of the renewable resource, the unit price (or cost) of brown electricity and the transport costs of the non-renewable resource to the thermal power plant. We also found that the green electricity price (and thus the level of brown electricity produced) increases with the population size, the share of the total land area devoted to green energy production and the price elasticity of land. In Indonesia, coal-fired power plants are increasingly satisfying the rising demand for electricity. Our model results suggest that the increasing population density in Indonesia over time causes a reduction in green electricity production and thus a falling share of green electricity production in the total electricity supply. We showed that, until 2050, the expected population growth in Indonesia leads to about a 35% reduction of the country's share of electricity produced with renewable energy sources (from 12.8% in 2016 to 8.2% in 2050). This reduction is accompanied by a decrease in the renewable exploitation area, suggesting competition between the need for renewable energy production and other needs, such as residential use. These results are not reversed with a substantially higher assumed power density of the renewable energy sources.

In Chapters 5 and 6 we analysed how city size and urban form affect residential energy use and emissions in Indonesian cities. Despite the importance of urban areas for energy use and global emissions, data on urban energy use are in short supply, especially when it comes to urban areas in the global South. An important finding in the literature on the relationship between urban form and energy use is that both increasing urban density and increasing city size reduce households' average energy consumption (see, e.g., Glaeser and Kahn, 2010). The basic idea underlying this so-called compact city argument is that a higher population density makes cities more environmentally friendly, because it decreases the average commuting distance and increases the public transport usage, while smaller housing units help to reduce transport and home energy use. However, to the best of our knowledge, this line of argument has not been tested in the context of developing countries, in which the involved mechanisms may lead to different outcomes, especially in countries that combine low incomes and rapid urbanization.

We contributed to this research by conducting an empirical analysis of the role that city size and urban density may play in driving urban energy use in Indonesia. To this aim we developed two datasets. Our first dataset was constructed on the basis of data from the Indonesian National Statistics Office, and brought together urban indicators for 71 cities across Indonesia. Our second dataset was built on information that we collected ourselves through a survey of 748 households in 2016, and included household-level information across 45 districts within the metropolitan area of Yogyakarta. In Chapter 5 we used the first dataset and a two-stage regression model, to test whether urbanization influences per capita energy consumption per se, that is, beyond the ability of urbanization to explain increasing energy use through its influence on per capita incomes. Using the second dataset and the two-stage regression approach developed by Combes et al. (2008), we examined the extent to which the observed impact of urban indicators on energy consumption is influenced by the spatial sorting of people within a large metropolitan area.

In short, we found no evidence that in Indonesia larger and denser cities have a direct effect on energy use other than through an income effect. The income effect is substantial, and city size has a significant positive effect on per capita energy expenditure – supporting the existence of positive agglomeration externalities. But, we did not find a statistically significant impact of population density on energy expenditure. Within the metropolitan area of Yogyakarta, we found that urban characteristics play an important role in explaining energy use – household characteristics explain only about 40% of the per capita total energy consumption and per capita energy consumption for transport, whereas they explain only about 20% of the per capita dwelling energy consumption. Our regression results showed that the distance to the city centre – which is correlated with the population density – plays a crucial role in explaining the within-city variation in energy consumption. People who live closer to the city centre (in a denser district) tend to consume less energy, because their relatively short commuting distance saves energy consumption for transport. We also found an indication that people who live far from the city centre consume less energy, that is, electricity, in their dwelling. In other words, using cross-city data, we found no support for the compact city hypothesis (Glaeser & Kahn, 2010), but we did find support for this hypothesis within the metropolitan area of Yogyakarta.

In Chapter 6 we analysed the influence of urban form on motorcycle choice in comparison with other transport modes, employing a multinomial logistic (MNL) regression model an ordinal logit regression (OLR) approach, and using data from our survey across households in the metropolitan area of Yogyakarta. We also examined the impact of urban form on households' ownership of motorcycles in comparison with cars. We found that the urban form explains about 20% of the observed variance in transport mode choice, while it explains less than 6% of the observed variance in the probability of household ownership of motorcycles and cars. Population density has a statistically significant positive effect on the likelihood of using a motorcycle in commuting. People who live near the city centre have a higher probability of travelling by car than by motorcycle; in contrast, people who live far from the city centre have a higher tendency to travel by bicycle than by motorcycle. In other words, the likelihood of choosing a motorcycle over other transport modes is highest for intermediate distances between the home and the city centre – this distance effect is, however, relatively small. In contrast to our results for the transport mode choice, the population density has no significant effect on households' ownership of private motor vehicles, including motorcycles. In addition, the impact of the distance between the home and the city centre on the household ownership of private motor vehicles appears to be insignificant. We also found that the travel distance in general does not influence the household ownership of motorcycles, but it does exert a positive impact on the ownership of a car.

In general, the effect sizes that we found in our empirical analyses as presented in Chapter 5, clearly show that the (positive) effect of income on energy consumption or expenditure dominates the potential decelerating effects of urban form. Hence, if urban incomes in Indonesia continue to rise, future energy consumption in Indonesia is expected to increase substantially, since the vast majority of people in Indonesia prefer to commute by motorcycle. This also implies a substantial increase in future greenhouse gas emissions and local air pollution. This will pose huge challenges in combatting climate change, for which large-scale investments in public transport and electric motorcycles provide promising but costly policy directions.

Of specific interest in developing countries is the transport system (which is the focus of Chapter 6). Everyone who has ever been in an Indonesian city – and especially in Jakarta – will vividly remember the motorcycles that you literally see everywhere in the heavy congested city. Also in other cities, motor cycles are intensively used for daily transport. According to Statistics Indonesia (2018), in 2017, the total number of passenger car and motorcycle was estimated 15.4 million and 111.5 million respectively and the total number of household was 67.2 million. Hence, in average each household in Indonesia has more than one motor vehicle. In Yogyakarta, the city that we surveyed, the motorcycle is by far the dominant mode of urban transport: 95% of the households in Yogyakarta own a motorcycle and almost 30% of the households own more than two motorcycles. Motorcycles are the preferred transport mode for 66% of the commuters in Yogyakarta. For buses and bicycles, this percentage is, respectively, 2% and 9%. Hence, encouraging substitution away from the usage of private motorized vehicles towards public transportation, like the one offered by the Trans-Jogya service, or non-motorized transport modes – with the aim of decreasing the energy consumption and emissions from transport – is evidently a huge challenge.

A promising policy option therefore is to encourage users of motorcycles powered by oil fuel to move to electric motorcycle/bicycle. Although it would not reduce the congestion, it can substantially contribute to decrease the pollution and improve air quality. Despite that motorcycle consumes fuel more efficiently than cars, the prevalence of motor bikers results in motor cycles contributing more to fuel consumption than cars. Based on our survey in Yogyakarta, Chapter 6 came to the conclusion that motorcycles contribute 66% of total CO_2 emissions that come from transport. Until now, the market share of electric motorcycles in Indonesia has been very small, due to an inadequate supporting infrastructure, the unclear regulation for electric vehicles, the relatively high price and the short lifetime of the battery for electric motorcycles/bicycles, the relatively long time required for refueling compared with conventional motorcycles and the limited travel distance, power and speed (Jeghesta, 2016; Ravel, 2016). Thus, given the large number of motorcycles in urban areas in Indonesia, stimulating the growth of the market for electric motorcycles or even bicycles is in principle a potentially promising urban policy strategy. This, however, requires that the Government seriously develops the supporting infrastructure, such as providing charging units in public places, office centres and residential areas; increasing the number of dealers and service shops of electric motorcycles/bicycles, finishing the regulation formulation for electric motorcycles and considering the provision of subsidies to encourage people to purchase electric motorcycles/bicycles.

Our results in Chapter 6 suggest that a compact urban form, including a high population density and short travel distances, may help in reducing the (growth of) motorcycle use in urban areas. This evidence supports the notion that reducing CO_2 emissions intensity is not only a matter of technology adoption, but also of changes in behavior by consumers as well as the government. For example, the government or any private institution such as NGO could also try to stimulate behavior change programs such as encouraging people to use public transportation more frequently instead of private vehicles. However, this effort will be very difficult, if not impossible since people's behaviors are influenced by cultures (Sasmojo, 2004) and cultures tend to remain unchanged (Hofstede, 2001).

Another policy route is to invest in improved and intensified practices of spatial planning and infrastructure development (Heiskanen et al., 2010). Providing available infrastructure is, however, difficult since usually it needs a big investment and takes a long time. In addition, the Indonesia government could invest in developing programs to switch the fossil fuel subsidy into programs which could deter the negative impact of the subsidy decrease. The Indonesia government could learn from their failures on cash transfer program in 2005 and 2008 (World Bank, 2012). With additional money from the subsidy cutting, the Indonesia government should enhance better social assistance programs that have been developing in the last few years and create such new programs. Joko Widodo, the Indonesia president, wanted to transfer the subsidy into productive sectors (Tamindael, 2014).

The programs could also be expanded into programs to diminish the negative impact of urbanization. The government policy that in the long-run might be able to reduce the negative effects of urbanization is the village fund program. Started in 2015, the objectives of this program include development and empowerment of people in the village (Indonesian MF, 2019). Joko Widodo is also making programs to develop regions in outside Java because for long decades it is known that the development between Java and outside Java is not equal. Many people from outside Java are attracted to move to Java because Java offers lots of good facilities on education, health, utilities, transport sector, etc. In the transport sector, Joko Widodo also drives the development of many highways or toll roads in Java and outside of Java. The highways should be able to reduce congestion and speed up the distribution of goods. However, this policy also reaps criticism because several people feel that the toll tariff is too expensive for poor people (Ihsanuddin, 2018) and that the developments that are paid by debt increase the burden on the Indonesian budget (Sukmana, 2019). Joko Widodo also has a plan to relocate the (administrative) capital city from Jakarta to East Kalimantan (Sang, 2019). The program is expected to decrease the burden on crowded and highly polluted Jakarta and also to develop the area outside Java. The president dreams to have a new smart capital city with less emissions and a friendly public transportation system (Bhwana, 2019).

Satisfying all parties is impossible. Efficiency and equality are a big trade-off for policy makers. Any policies should be evaluated on its impact in the long-term. It should support a sustainable development. At the same time, the authorities should also try to minimize its negative effects, especially with regards to the accessibility for all.

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SUMMARY

This thesis aims to contribute to the study of interactions between global environmental change, economic development and the spatial structure of the economic system in developing countries. The research presented in this thesis focuses on Asian countries, with a specific focus on Indonesia.

Countries in the global South play a key role when it comes to the need of reconciling expansion of the world economy with global environmental sustainability. Economic development is accompanied by urbanization and both processes are fueled by access to modern energy sources. If these sources mainly consist of fossil fuels, energy consumption will continue to be a main driver of local air pollution and global greenhouse gas emissions. Consequently, these countries therefore face a major dual 'energy challenge': the simultaneous expansion and greening of their energy supply. Against this background, this thesis presents a set of different studies into the relationship between energy use and the spatial structure of economic development.

In Chapter 2 we developed a meta-analysis of previously published empirical studies on the so-called Environmental Kuznets Curve (EKC) – an inverted U-shaped relationship between income and emissions – to shed new light on the long-lasting debate on the income-emission relationship (IER). In Chapter 3 we tried to identify the role of cultural values in a society in determining the income-emission relationship across a sample of Asian economies. Since CO_2 emissions result from human activities, cultural values can be thought of as (implicit) drivers of CO_2 emissions.

In Chapters 4, 5 and 6 we focused on the role of cities in defining the interaction between global environmental change and economic development. In Chapter 4 we developed a spatial energy model to analyze the potential trade-off between greening and brown expansion of the electricity supply in developing countries under the influence of increasing population density. The model builds on the concept of an energy source's power density in watts per square metre (W/m^2) as measure of a resource's 'spatial productivity'. Power density differs between renewable energy and fossil fuels. A non-renewable resource (like coal) is more power dense and hence spatially more productive than a renewable resource (like solar), which, all things

being equal, implies that it is cheaper to transport fossil fuels. We calibrated the model to the case of Indonesia. In Chapter 5 we analyzed urban energy-use patterns across Indonesia. Based on a dataset for 71 Indonesian cities that was constructed from existing household surveys and census data, we investigated whether urbanization influences the per capita energy consumption, controlling for the impact of urbanization on per capita incomes. In addition, we analyze the spatial patterns of energy consumption across districts within the metropolitan area of Yogyakarta, one of Indonesia's largest cities. The latter was done on the basis of a survey on energy consumption and travel behavior that we conducted among 748 households in Yogyakarta Province. Finally, in Chapter 6 we used the results from this field study to analyze the way in which urban form influences preferences for the use and ownership of motorcycles in the metropolitan area of Yogyakarta.

The main findings of this dissertation are as follows:

1. *There is evidence supporting the hypothesis of an inverted U-shaped relationship between income and emissions, the so-called Environmental Kuznets Curve (EKC).* By collecting 919 estimates from 136 published studies on the Income-Emission Relationship (IER), this dissertation found that the percentage of observations with positive slopes of the IER curves in our database is increasing at lower levels of GDP per capita, but decreasing for higher GDP per capita. The meta-analysis study shows that the likelihood of finding evidence for an EKC is larger when a study uses data for developed countries and employs variables controlling for trade and environment. The likelihood of finding evidence for an EKC is lower in studies published in prominent journals or in journals that have an SJR ranking (but the higher the SJR ranking of a journal, the larger the probability of finding evidence for an EKC). In line with the meta-analysis results, based on an own primary study this dissertation found that per capita income has a statistically significant positive effect on the CO_2 emission intensity, but the EKC theory cannot be proven based on a mixed-effect regression model with random effects at the country level using data for nine emerging Asian countries during the period 1972–2014.

2. *Technological progress, the usage of green energy and higher fuel prices foster the decrease of the CO_2 emission intensity, but this is partly counteracted by an increase of per capita CO_2 emission intensities caused by the growth of population size and urbanization.*

   The mixed-effect regression model developed in this dissertation also shows that technological advances, higher share of green energy and higher fuel price significantly reduce the CO_2 emission intensity. However, per capita CO_2 emission intensities increase with population size and urbanization. Thus, whether technological advances, which can also be reflected in term of the utilization of green energy, could reduce the CO_2 emission intensity will also depend on how fast population and urbanization grows.

3. *Cultural factors can significantly affect the CO_2 emission intensity.*

   Cultures influence people's behaviour and thus may affect the CO_2 emission intensity. Based on the model developed using data from nine emerging Asian countries during 1972–2014, this dissertation found that countries with a high degree of power inequality in terms of reputation, riches and authority, countries whose societies tend to avoid uncertainty, countries whose societies have lower desire to compete for the best, high achievement, etc. and have higher desire to cooperate and support each other, be humble, etc., and countries having high societal norms in limiting the needs for pleasure in life, tend to have a lower CO_2 emission intensity. When corrected for income, people with higher individualism characteristics and people with long-term orientation tend to have lower CO_2 emission intensity.

4. *High population growth may lead to a decreasing share of electricity produced with renewable energy sources.*

   This dissertation developed a deterministic partial equilibrium model of the electricity supply chain, in which the demand for electricity in a large city can be satisfied by a non-renewable ('brown') energy fuel, a renewable ('green') energy source or both. We calibrated the model to the case of Indonesia, to simulate the influence of population growth on electricity production generated from brown and green resources. Indonesia's scattered geography, the associated high costs to transport coal and its relatively 'clean infrastructure slate' may enable the country to exploit quickly a range of low-carbon alternatives. However, we found for Indonesia that the increasing population density over time causes a reduction in green electricity production and thus a falling share of green electricity production in the total electricity supply. Indeed, in Indonesia, coal-fired power plants are increasingly satisfying the rising demand for electricity. We showed that, until 2050, the expected population growth in Indonesia is predicted to lead to about a 35% reduction of the country's share of electricity produced with renewable energy sources. This reduction is accompanied by a decrease in the renewable exploitation area, suggesting competition between the need for renewable energy production and other needs, such as residential use.

5. *In Indonesia larger and denser cities have no direct effect on energy use other than through an income effect.*

   Using data across cities in Indonesia, this dissertation found no evidence that larger and denser cities – the so-called compact city theory – have a direct effect on energy use other than through an income effect. The income effect is substantial: a 1% increase in the per capita income increases the per capita total energy expenditure by 0.38%, per capita energy expenditure on transport by 0.45% and per capita energy expenditure on dwellings by 0.35%. We also found a significant positive effect of city size on per capita energy expenditure but no effect of population density.

6. *Urban characteristics – especially distance to the city centre – play a role in explaining within-city variation in energy consumption.*

   Within the metropolitan area of Yogyakarta, we found that urban characteristics play an important role in explaining energy use; household characteristics explain only about 40% of the per capita total energy consumption We found that the distance to the city centre – which is correlated with the population density – plays a crucial role in explaining the within-city variation in energy consumption. People who live closer to the city centre (in a denser district) tend to consume less energy, because their relatively short commuting distance saves energy consumption for transport. We also found an indication that people who live far from the city centre might consume less energy, that is, electricity, in their dwelling. In general, however, the effect sizes that we found show that the (positive) effect of income on energy consumption or expenditure dominates the potential decelerating effects of urban form.

7. *The urban form does affect preferences regarding the transport mode.*

   We found that in the Yogyakarta metropolitan area the urban form explains about 20% of the observed variance in transport mode choice, while it explains less than 6% of the observed variance in the probability of household ownership of motorcycles and cars. The chance of people using a motorcycle is increasing with population density, travel distance and travel frequency. The chance of people using motorcycle also increases for people whose home is at an intermediate distance from the city centre; near the city centre the probability of travelling by car is higher, whereas far from the city centre people have a higher tendency to travel by bicycle. This distance effect is, however, relatively small.

This dissertation studies the challenges faced by developing countries to fulfill the energy demand needed for their development and at the same time to reduce the dependence on energy generated from brown resources and replace it with energy generated from green ones to decrease greenhouse gases that contribute to global warming. The central questions addressed in this dissertation are as follows: What is the shape of the income-emission relationship? How do cultural factors affect the energy consumption and thus the emissions? Does the population size hamper the development of the electricity generated from green resources? Does urbanization influence residential energy use? Do population density and urban form affect transport mode preferences? The study on the income-emission relationship is a meta-analysis of existing studies, while the impact of cultural factors is studied using data from some emerging countries in Asia. The other studies are based on data from Indonesia.

Sotya Fevriera was born on February 19, 1974, in Salatiga (Central Java, Indonesia). She studied Statistics at Gadjah Mada University in Yogyakarta (Central Java, Indonesia), and Development Studies at the Bandung Institute of Technology (West Java, Indonesia). She started her work on this dissertation at the Vrije Universiteit Amsterdam (the Netherlands) in 2012. She is currently a lecturer at Economics Department, Faculty of Economics and Business, Satya Wacana Christian University in Salatiga (Central Java, Indonesia).